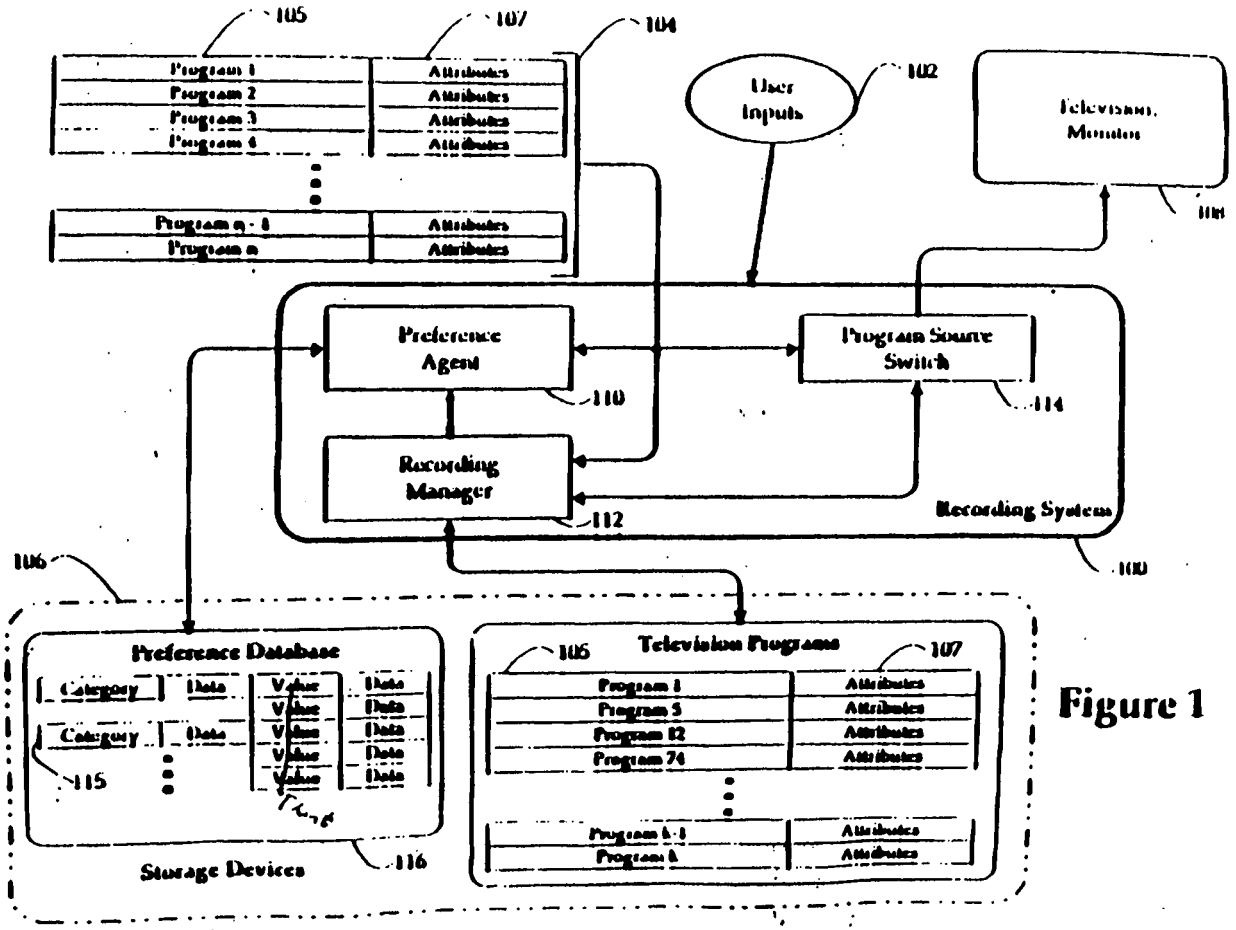

105
107
104
Program 1
Program 2
Program 3
Program 4
Attributes
Program n - 1
Program n
User Inputs
102
Television Monitor
Preference Agent
110
Program Source Switch
114
Recording Manager
112
Recording System
100
106
Preference Database
Category
Data
Value
115
Storage Devices
116
Television Programs
Program 5
Program 82
Program 74
Program k - 1
Program k

Figure 1

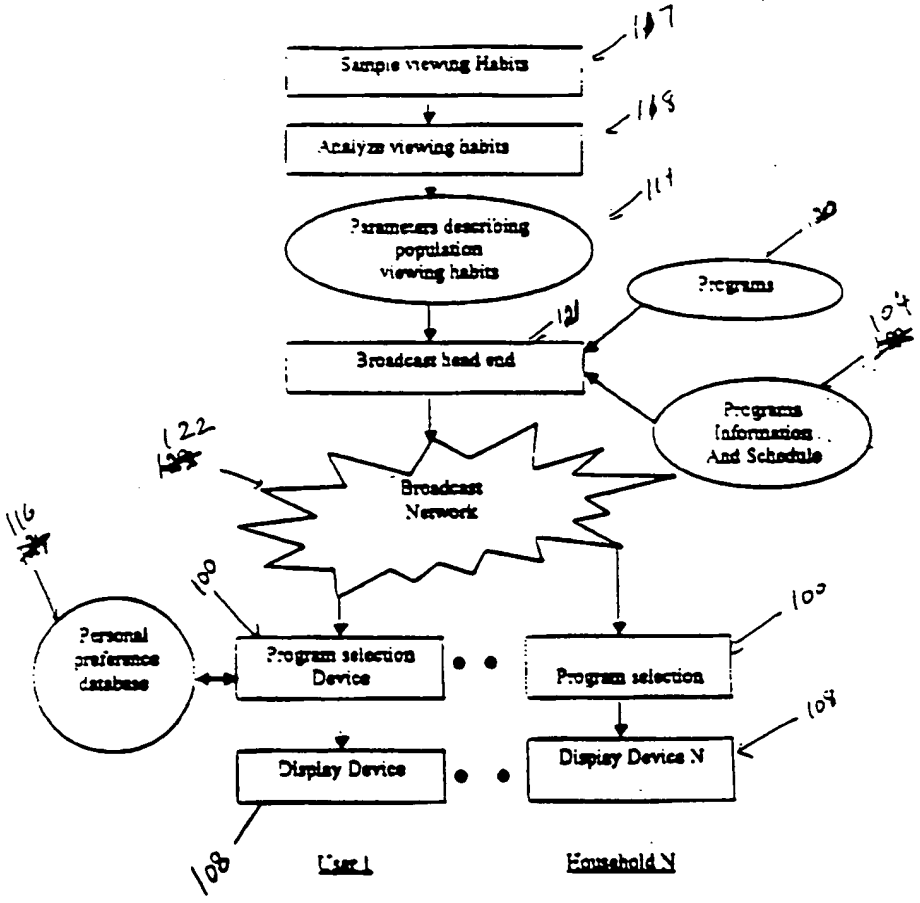

Sample viewing Habits
Analyze viewing habits
Parameters describing population viewing habits
Programs
Broadcast head end
Programs Information And Schedule
Broadcast Network
Personal preference database
Program selection Device
Program selection
Display Device
Display Device N
User 1
Household N

Figure 2

Examples of Program Information

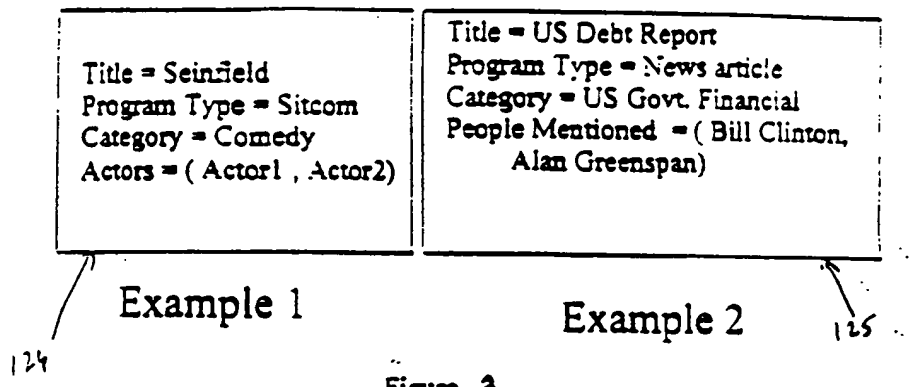


Figure 3

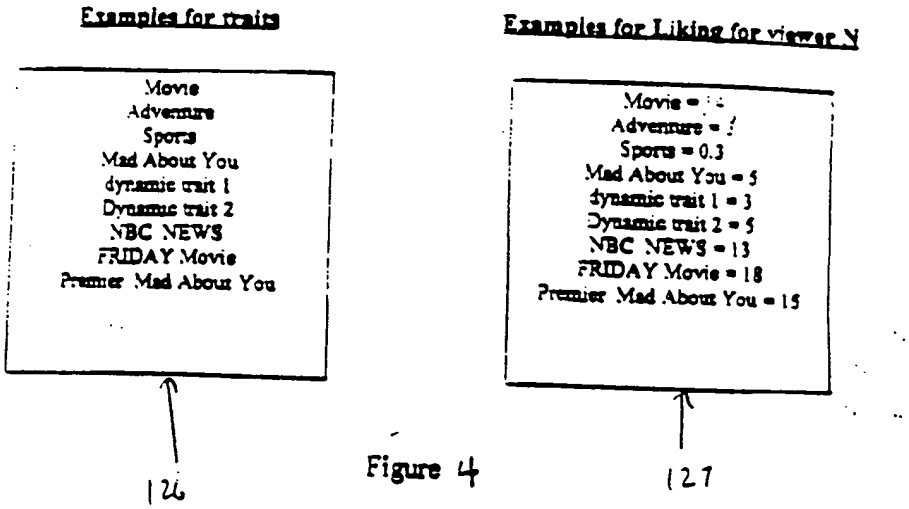

Examples for traits
Movie
Adventure
Sports
Mad About You
dynamic trait 1
Dynamic trait 2
NBC NEWS
FRIDAY Movie
Premier Mad About You
126
Examples for Liking for viewer N
Movie =
Adventure =
Sports = 0.3
Mad About You = 5
dynamic trait 1 = 3
Dynamic trait 2 = 5
NBC NEWS = 13
FRIDAY Movie = 18
Premier Mad About You = 15
127

Figure 4

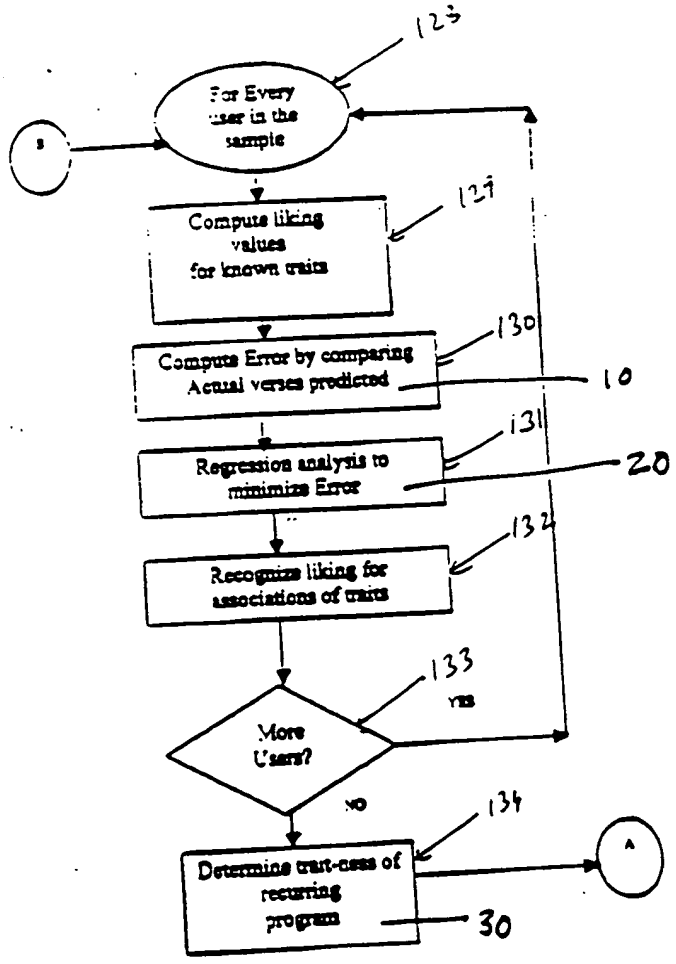

123
For Every User in the sample
B
Compute liking values for known traits
129
Compute Error by comparing Actual verses predicted
130
10
Regression analysis to minimize Error
131
20
Recognize liking for associations of traits
132
More Users?
133
yes
no
Determine trait-mass of recurring program
134
30
A

Figure 5(a)

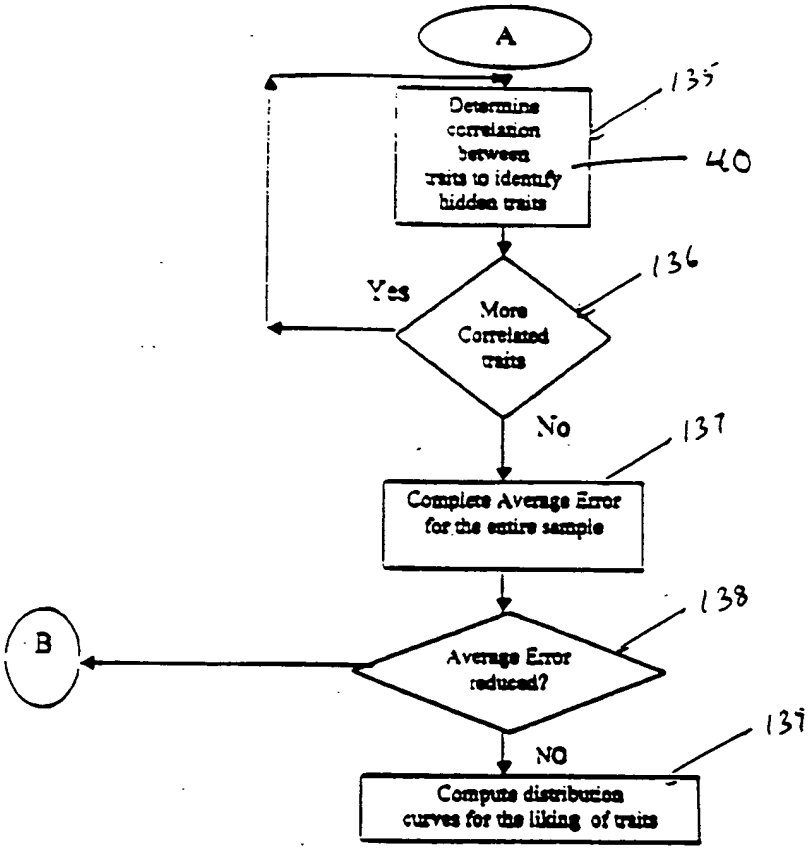

A
135
Determine correlation between traits to identify hidden traits
40
136
Yes
More Correlated traits
No
137
Complete Average Error for the entire sample
138
B
Average Error reduced?
139
NO
Compute distribution curves for the liking of traits

Figure 5 (b)

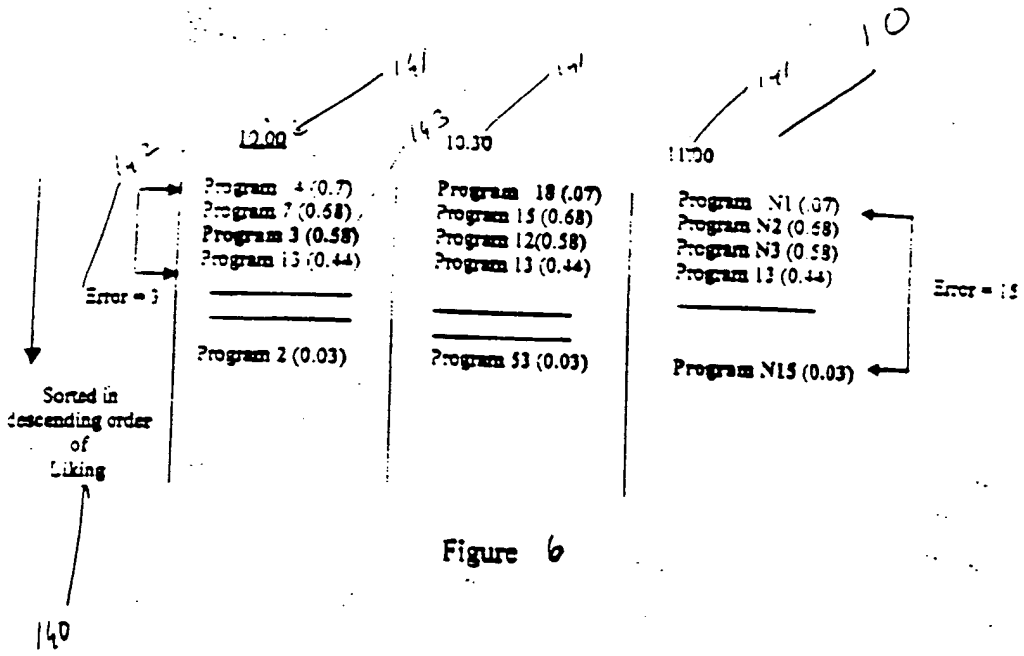
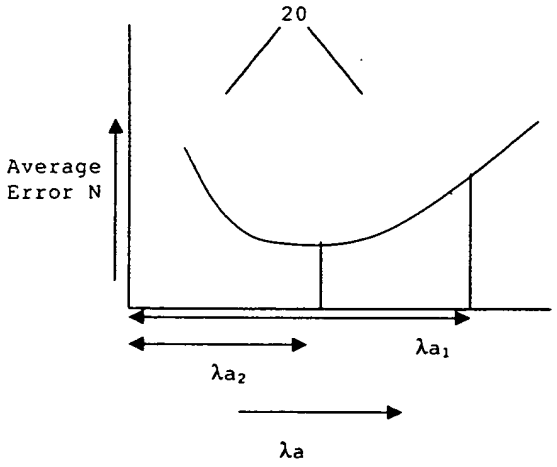

10
141
141
141
12:00
10:30
11:30
142
143
Program 4 (0.7)
Program 7 (0.68)
Program 3 (0.58)
Program 13 (0.44)
Program 2 (0.03)
Program 18 (.07)
Program 15 (0.68)
Program 12(0.58)
Program 13 (0.44)
Program 53 (0.03)
Program N1 (.07)
Program N2 (0.58)
Program N3 (0.58)
Program 13 (0.44)
Program N15 (0.03)
Error = 3
Error = 15
Sorted in descending order of Liking
140

Figure 6

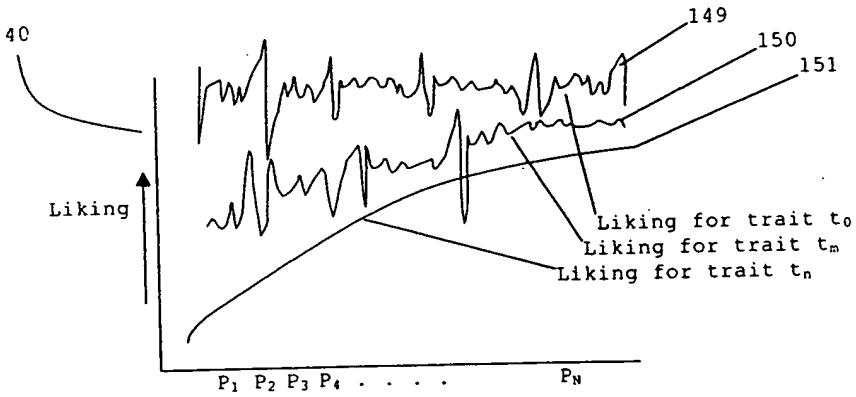
Figure 7

Current Liking Value	Next Liking Value
$\lambda a_1 = 2$	$\lambda a_2 = 1.5$
$\lambda b_1 = 5$	$\lambda a_1 = 5$
$\lambda c_1 = -3$	$\lambda a_1 = -3$
$\lambda d_1 = 0$	$\lambda a_1 = 0$



($\lambda b = \lambda b_1$
$\lambda c = \lambda c_1$
$\lambda d = \lambda d_1$
.
.
.)

Figure 8



t_m and t_n are correlated

t_m can be expressed as $t_m = t_x + t_m'$

and t_n can be expressed as $t_n = a_x t_x + t_n'$

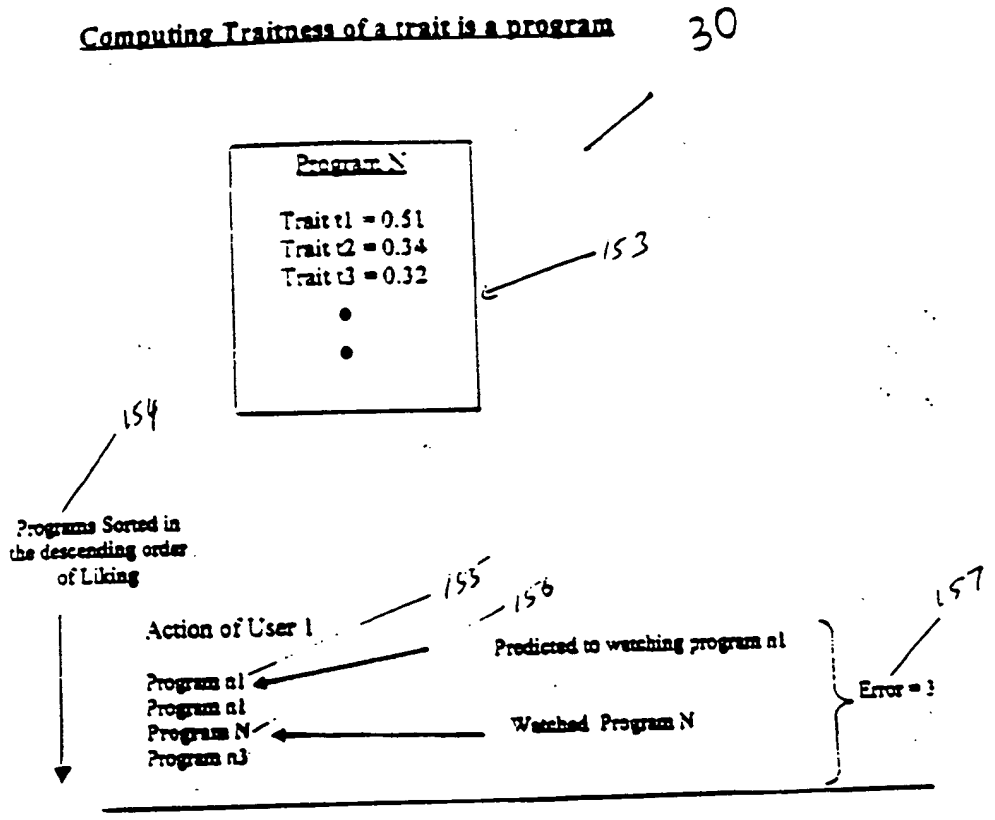

Computing Traitness of a trait is a program
30
Program N
Trait t1 = 0.51
Trait t2 = 0.34
Trait t3 = 0.32
153
154
Programs Sorted in the descending order of Liking
155
156
157
Action of User 1
Predicted to watching program n1
Program n1
Program n1
Program N
Program n3
Watched Program N
Error = 1

Figure 9(a)

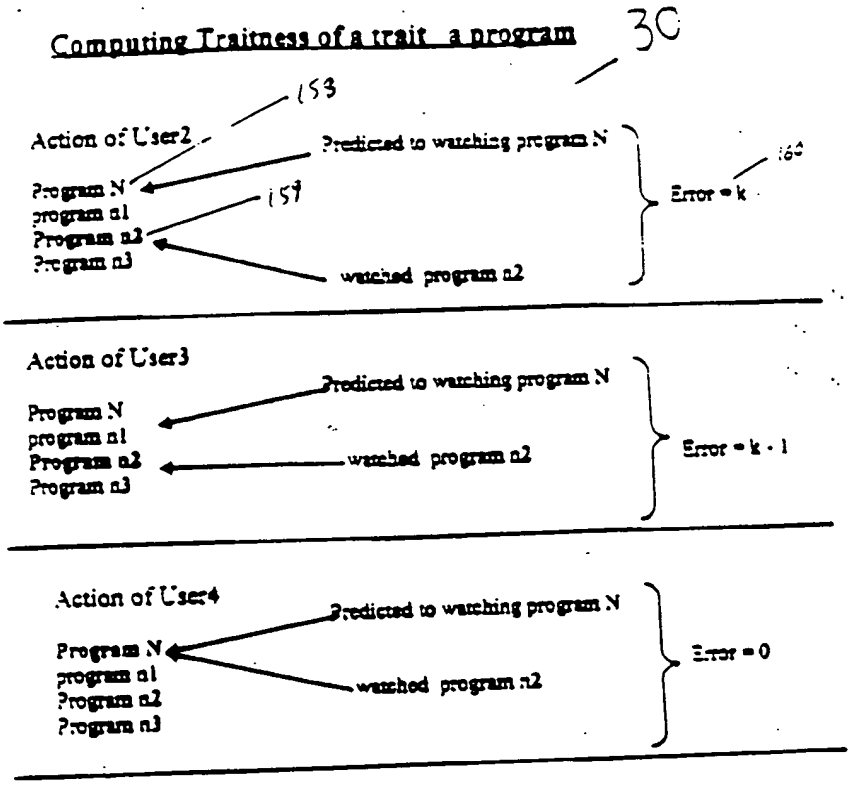
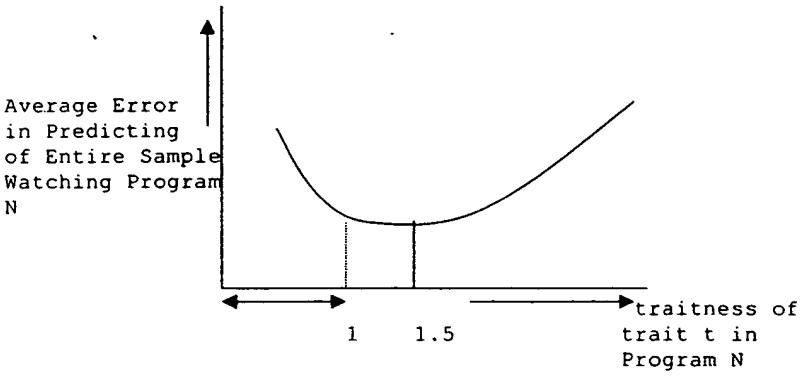

Computing Traitness of a trait a program
30
153
Action of User2
Predicted to watching program N
Program N
program n1
Program n2
Program n3
154
watched program n2
Error = k
Action of User3
Predicted to watching program N
Program N
program n1
Program n2
Program n3
watched program n2
Error = k - 1
Action of User4
Predicted to watching program N
Program N
program n1
Program n2
Program n3
watched program n2
Error = 0

Figure 9(b)

Figure 9(c)



Optimal value of traitness

e.g. comedy-ness in Seinfeld = 1.5
comedy-ness in Frasier = 0.89

Example for Liking Distribution Record format

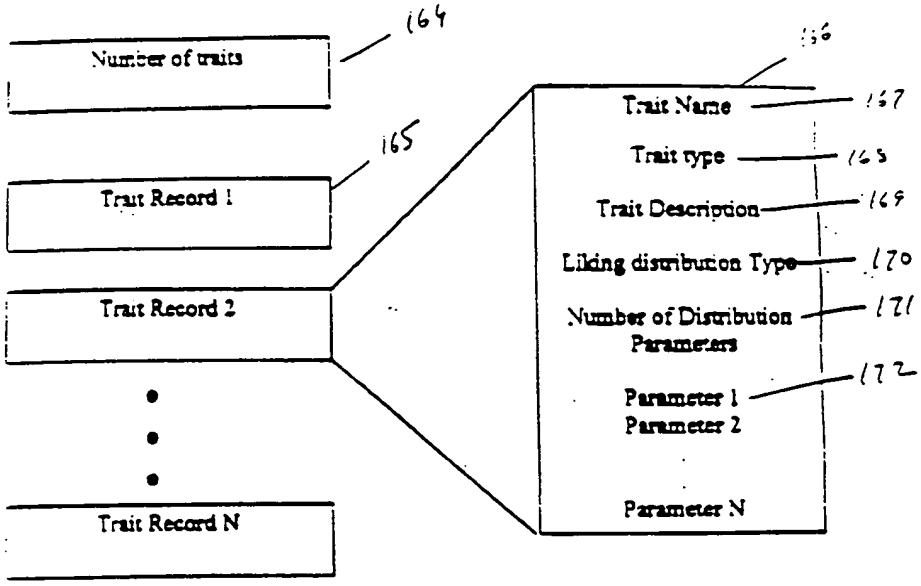


Figure 10

Some Sample Values For Fields in trait Record

Trait type	Trait Description
Static,	(NBC, "NEWS"),
dynamic	SUBSTRING("CIA") IN DESC,
Association	TITLE
Generated	

Distribution	Distribution Parameters
Normal	Mean = 13, Deviation =2
Exponential	
Defined type 1	
Defined type 2	

Figure 11

Example for Traitness of recurring Programs

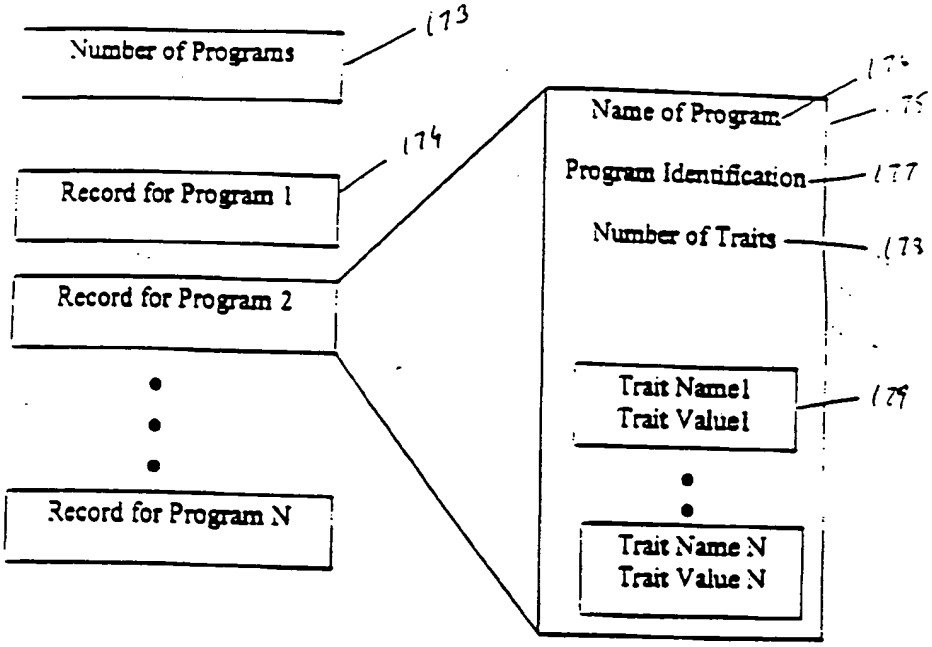


Figure 12

Example For Broadcasting traitness as a part of EPG Data

Program Info
Seinfield,
NBC ,
Comedy = 0.07
sitcom ,
Dynamic trait 1 = 0.1
•
•
Actor = Seinfield

Figure 13

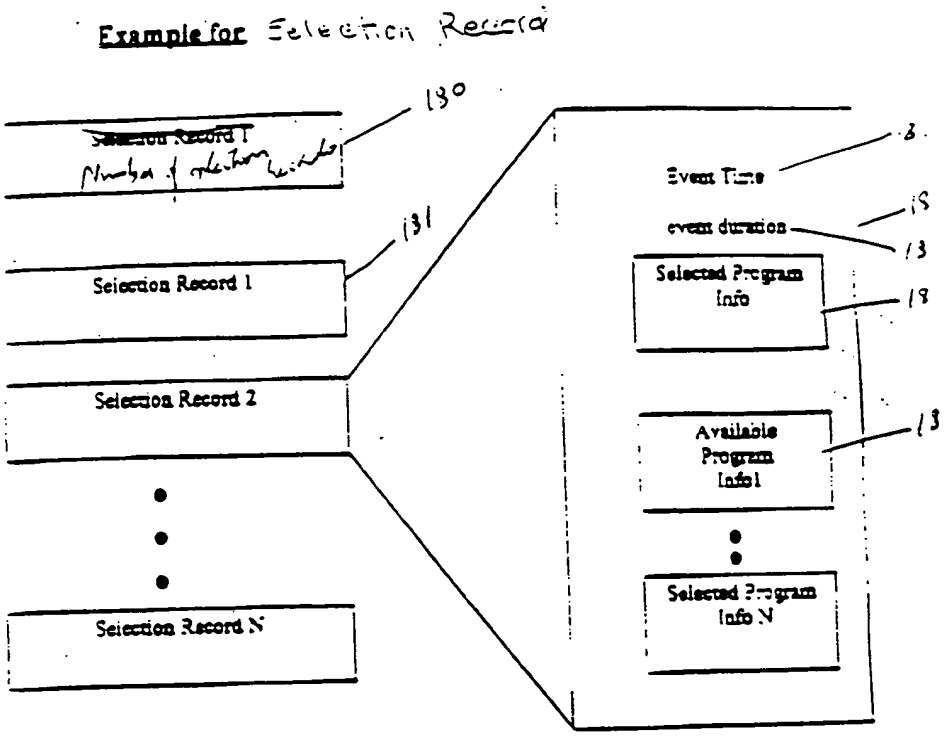

Example for Selection Record
130
Selection Record 1
Number of selection records
131
Selection Record 1
Selection Record 2
Selection Record N
Event Time
event duration
Selected Program Info
Available Program Info1
Selected Program Info N

Figure 14

Generation of User Selection History

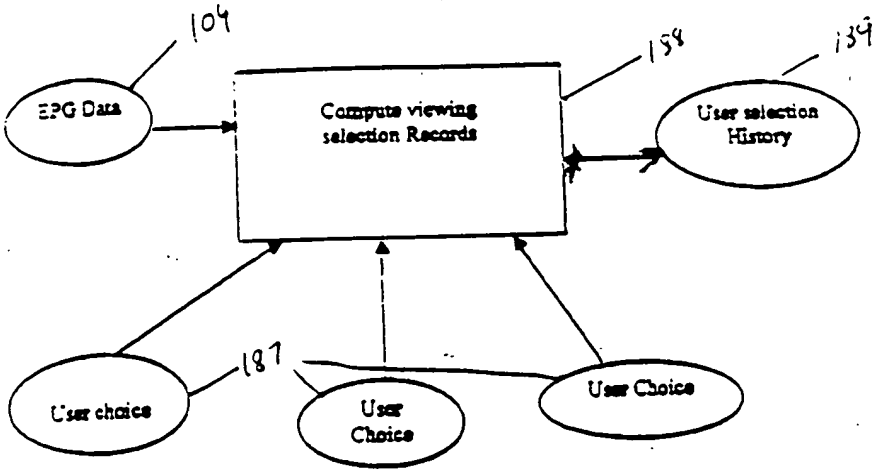


Figure 15

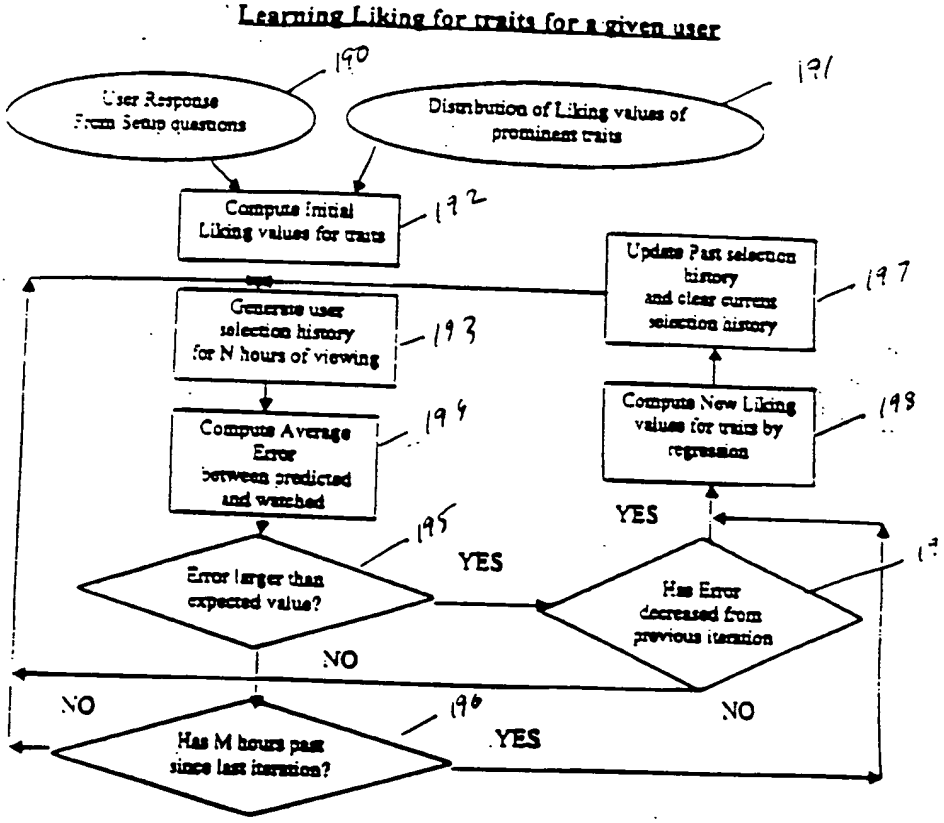

Learning Liking for traits for a given user
User Response From Setup questions
190
Distribution of Liking values of prominent traits
191
Compute Initial Liking values for traits
192
Generate user selection history for N hours of viewing
193
Compute Average Error between predicted and watched
194
Error larger than expected value?
195
YES
NO
Has Error decreased from previous iteration
YES
NO
Has M hours past since last iteration?
196
YES
NO
Compute New Liking values for traits by regression
198
Update Past selection history and clear current selection history
197

Figure 16

Computing Relevance

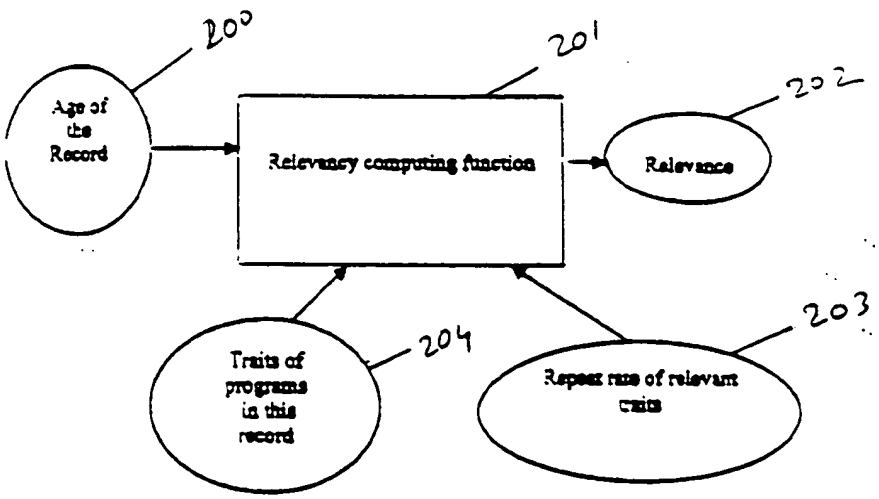


Figure 17 (a)

Figure 17(b)

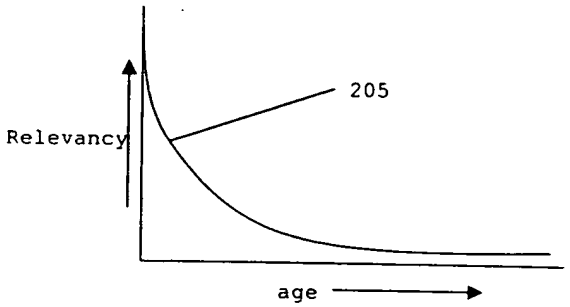
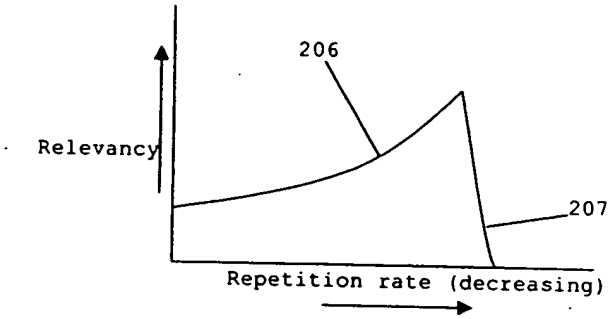


Figure 17(c)



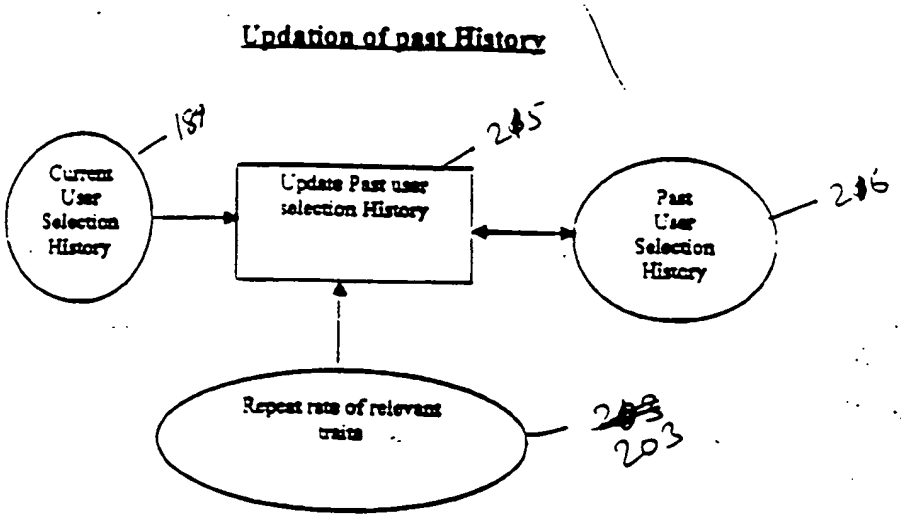

Updation of past History
Current User Selection History
Update Past user selection History
Past User Selection History
Repeat rate of relevant traits
203

Figure 18(a)

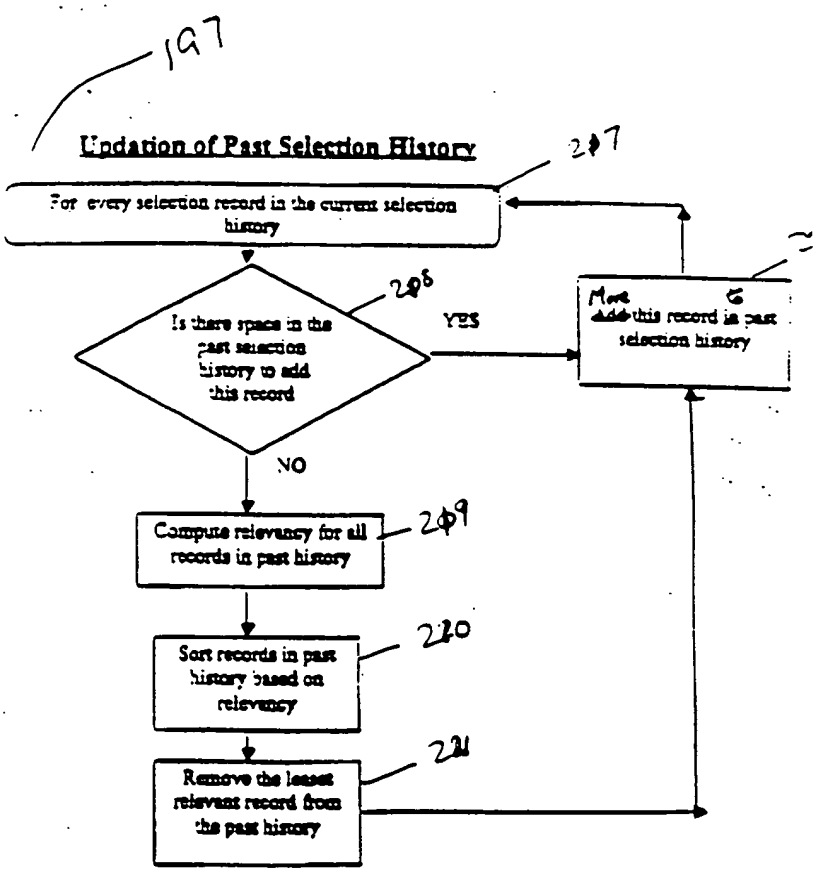

197
Updation of Past Selection History
207
For every selection record in the current selection history
206
Is there space in the past selection history to add this record
YES
Move & Add this record in past selection history
NO
209
Compute relevancy for all records in past history
210
Sort records in past history based on relevancy
211
Remove the least relevant record from the past history

Figure 18(b)

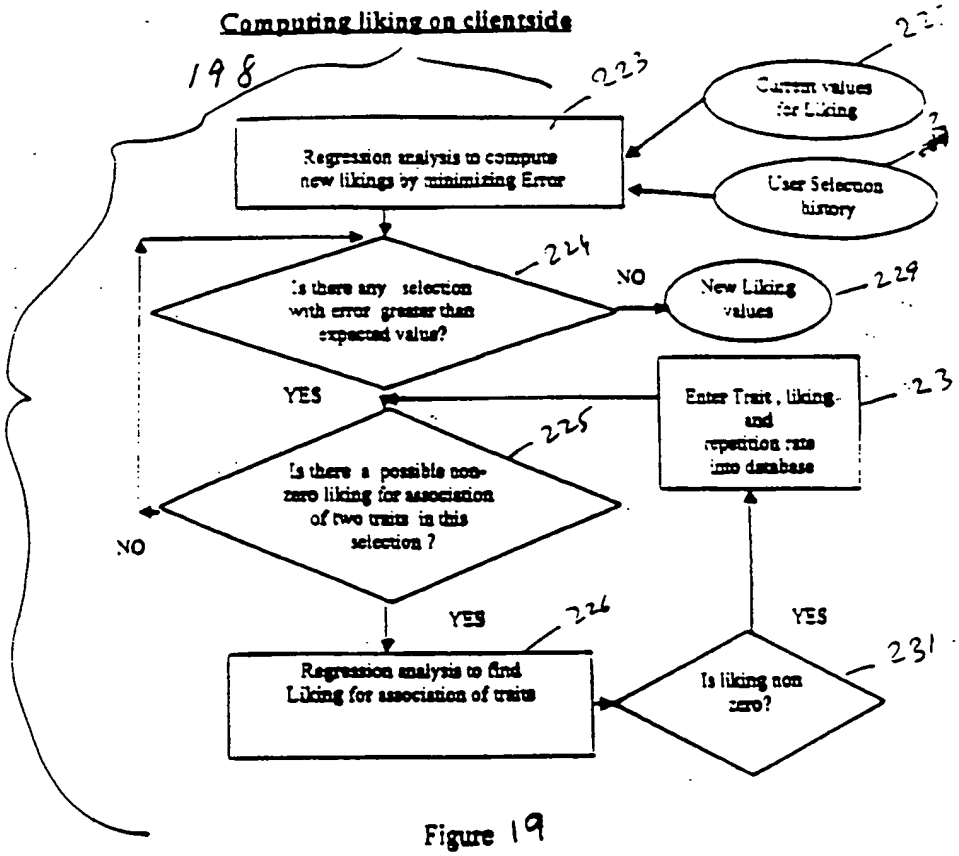

Computing liking on clientside
198
223
Regression analysis to compute new likings by minimizing Error
Current values for Liking
User Selection history
224
Is there any selection with error greater than expected value?
NO
New Liking values
229
YES
Enter Trait, liking and repetition rate into database
225
Is there a possible non-zero liking for association of two traits in this selection ?
NO
YES
226
Regression analysis to find Liking for association of traits
YES
Is liking non zero?
231

Figure 19

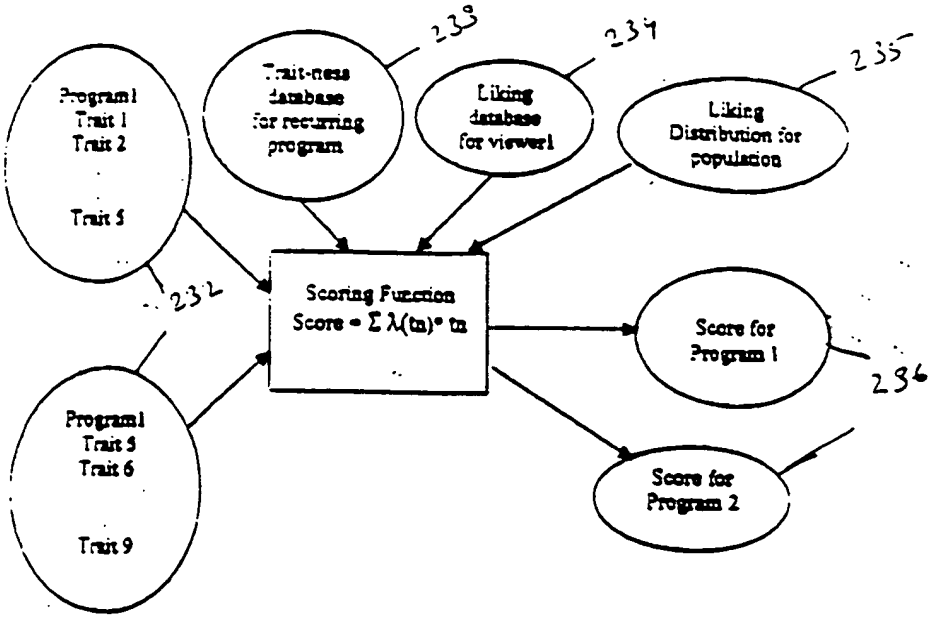
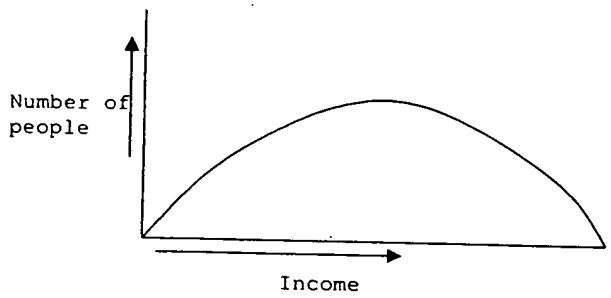
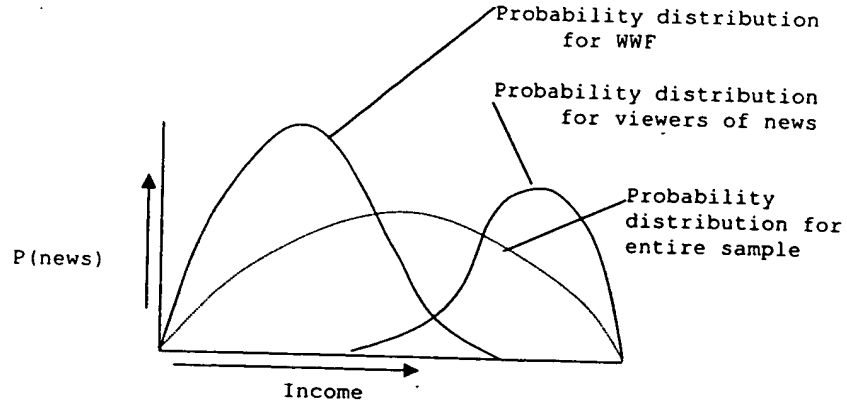

Computing scores for programs for future prediction
Program1
Trait 1
Trait 2
Trait 5
Trait-ness database for recurring program
Liking database for viewer1
Liking Distribution for population
Scoring Function
Score = Σ λ(tn)* tn
Score for Program 1
Score for Program 2
Program1
Trait 5
Trait 6
Trait 9
232
233
234
235
236

Figure 20

Figure 21(a)

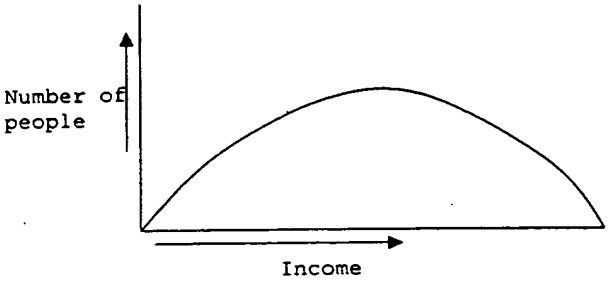


(i)

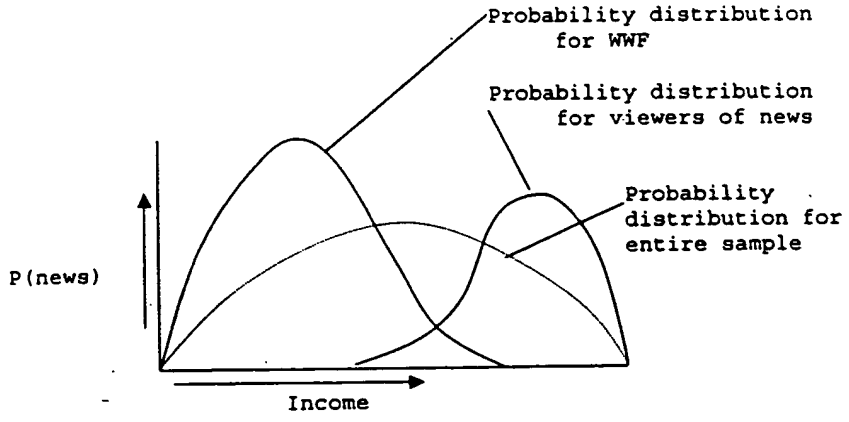


(ii)

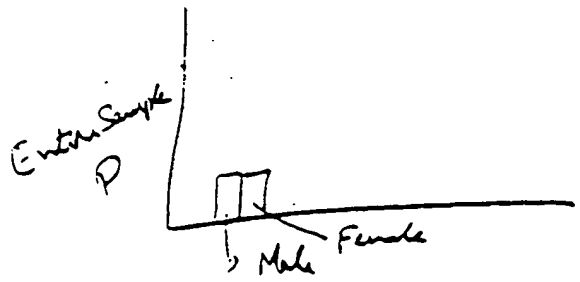
Figure 21(a)

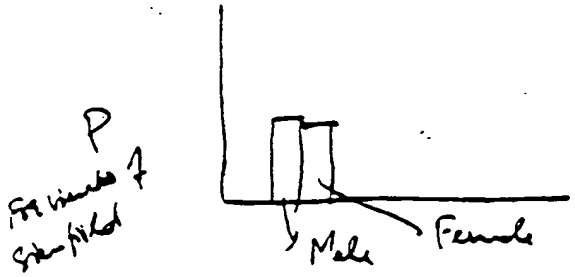


(i)



(ii)





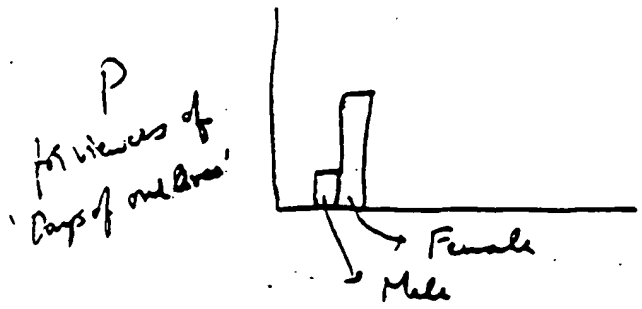


FIGURE 21b

System Architecture

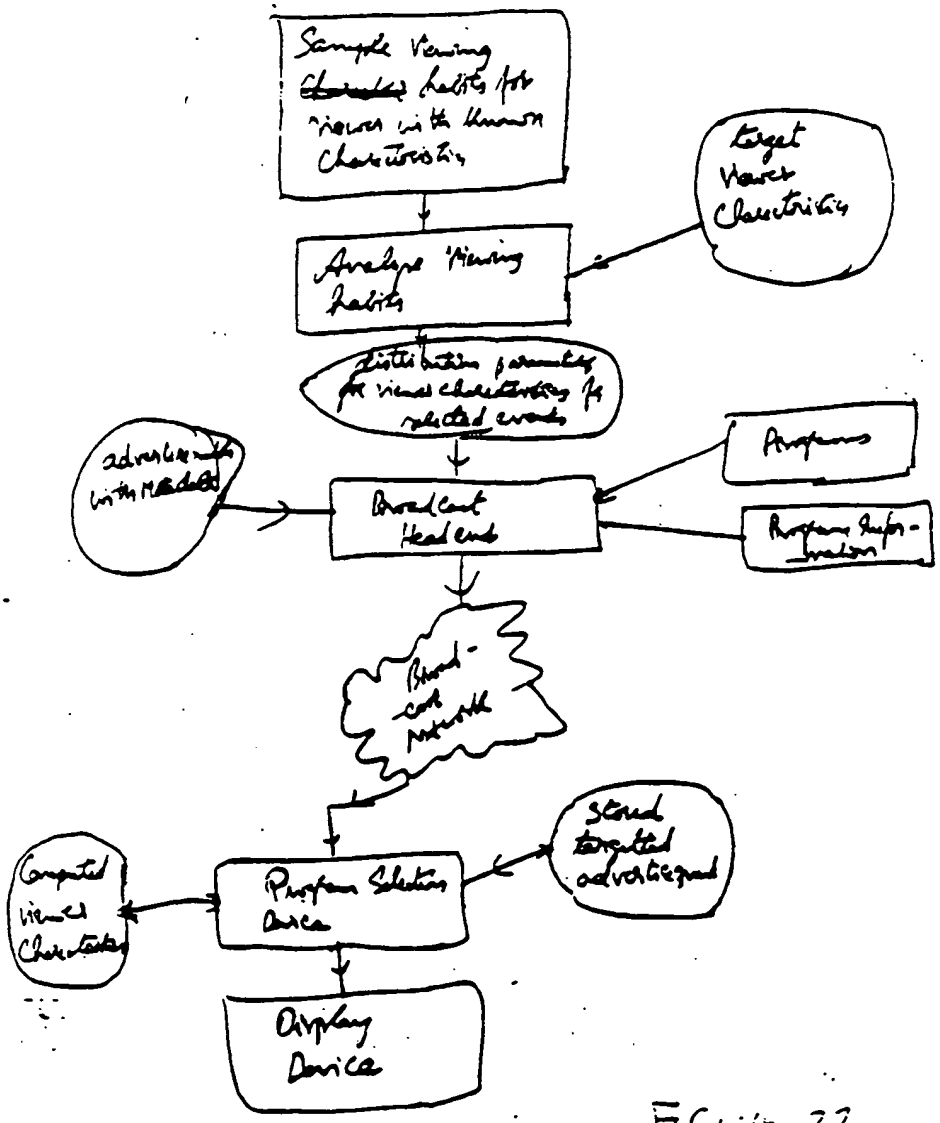


FIGURE 22

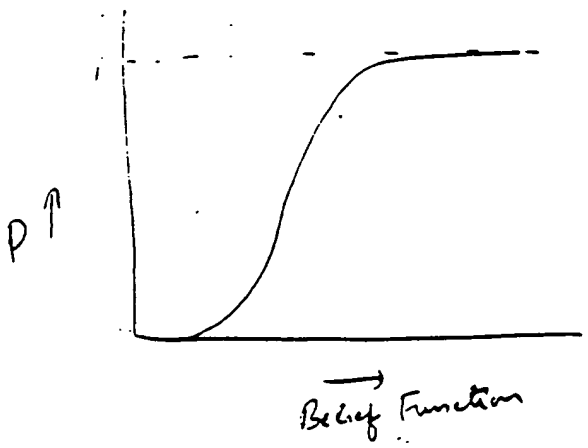


Figure 23a

Demographic Trait Record format

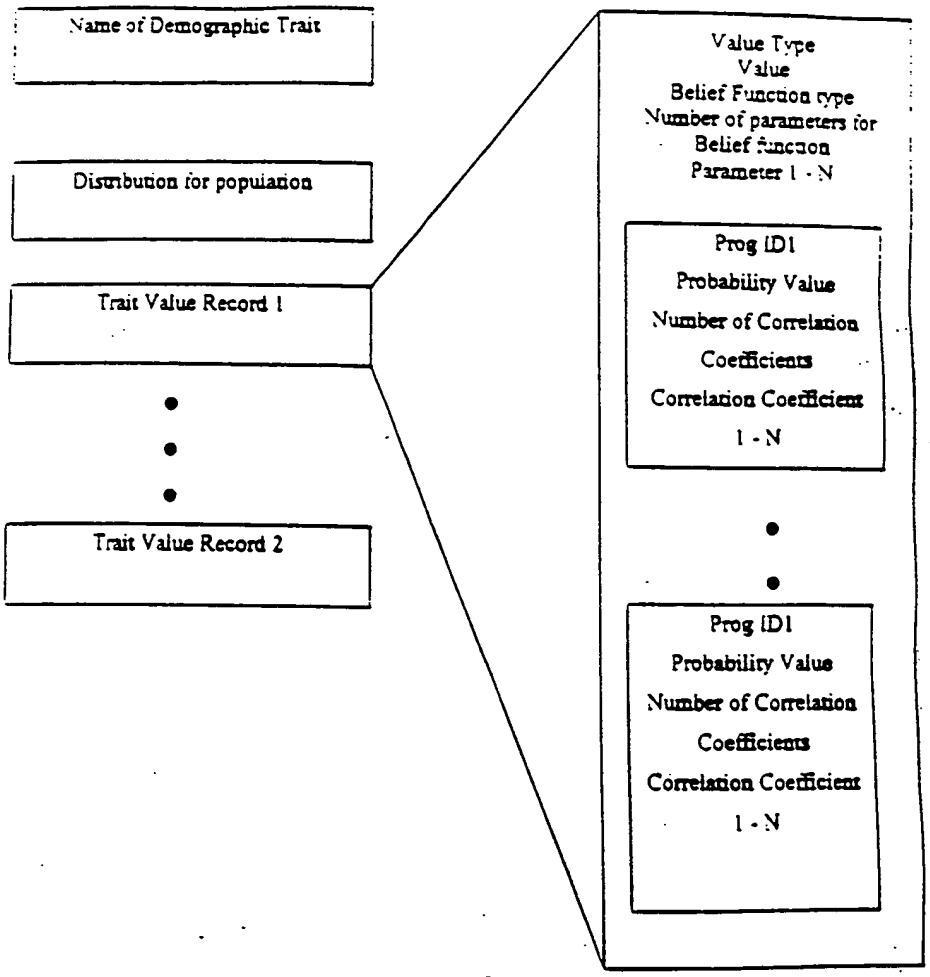


Figure 23b

Advertisement Targeting Record format

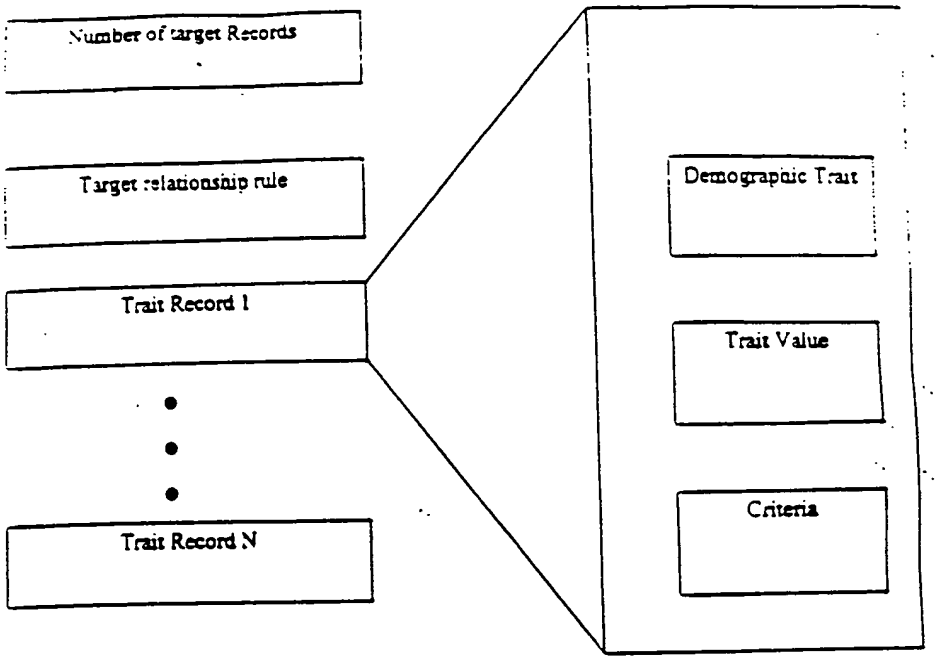


Figure 23C

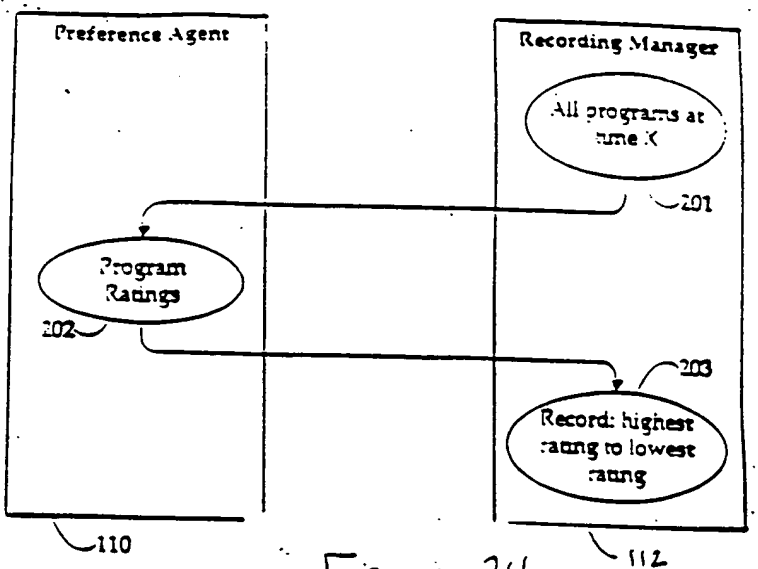


Figure 24

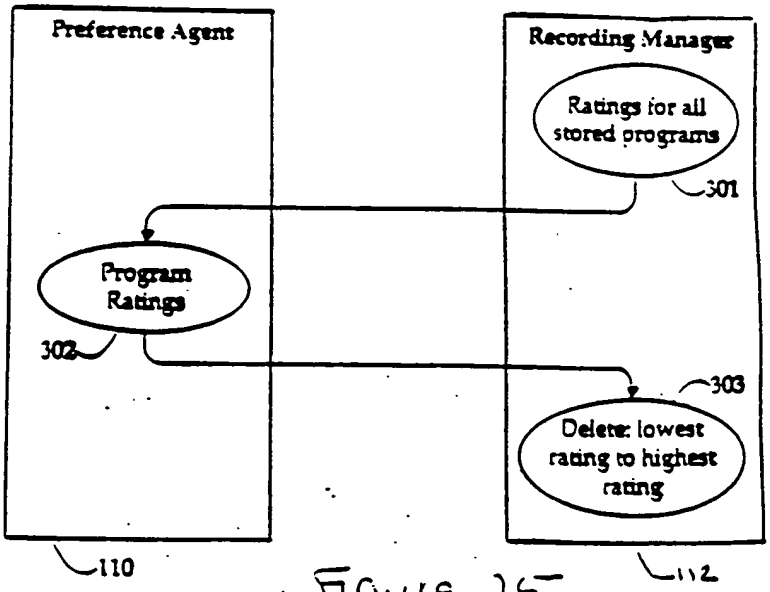


Figure 25

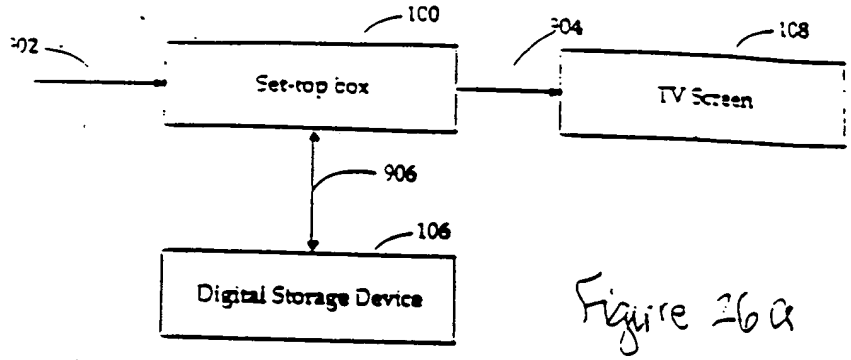


Figure 26a

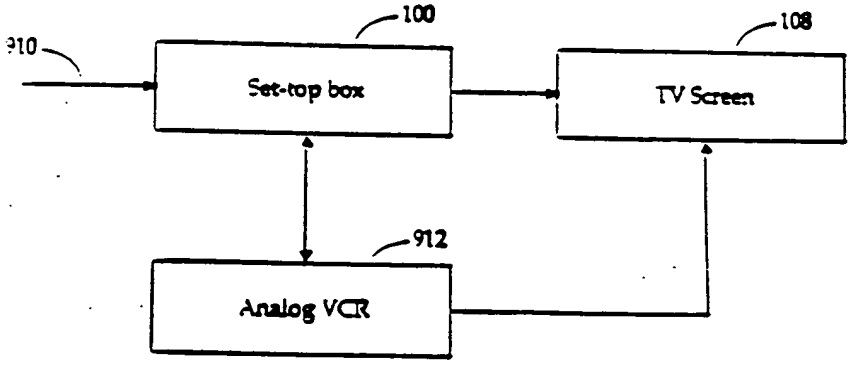


Figure 26b

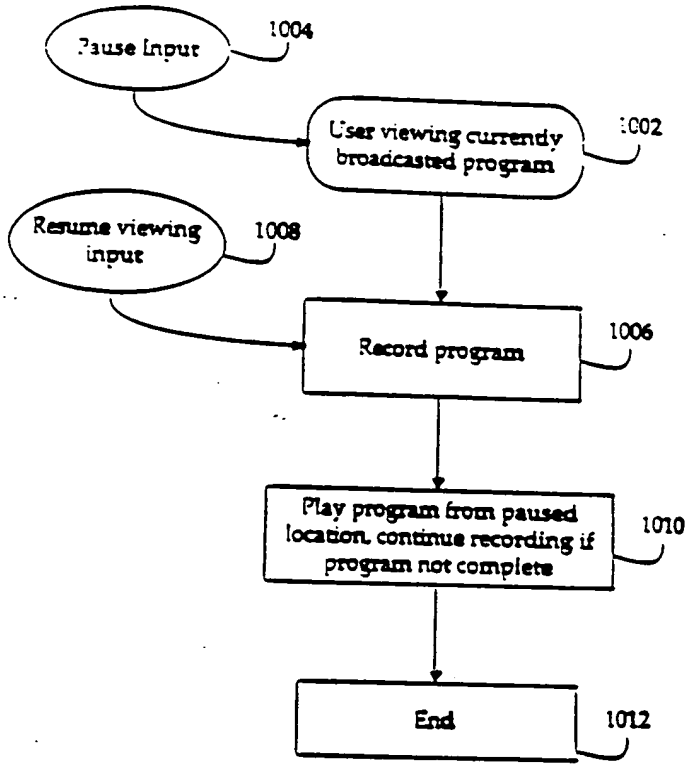

Pause Input
1004
User viewing currently broadcasted program
1002
Resume viewing input
1008
Record program
1006
Play program from paused location, continue recording if program not complete
1010
End
1012

Figure 27

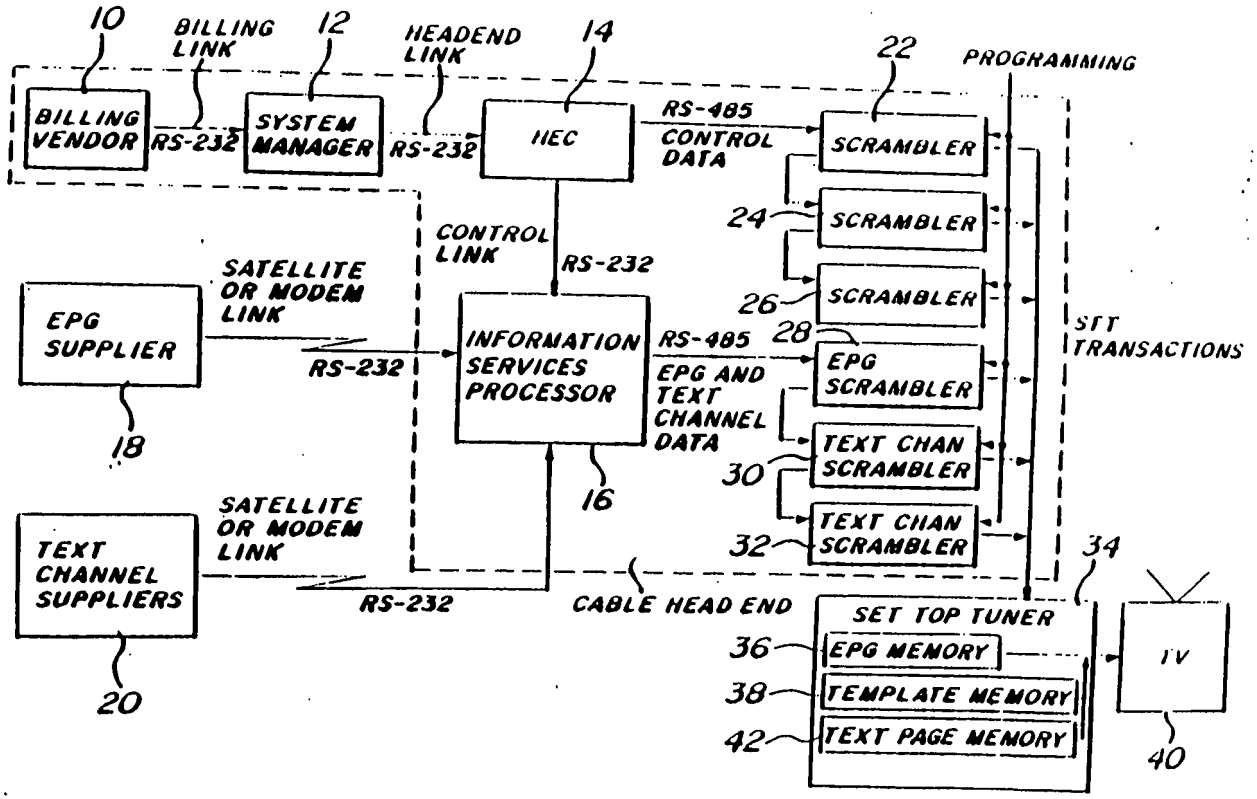

10
BILLING LINK
12
HEADEND LINK
14
22
PROGRAMMING
BILLING VENDOR
RS-232
SYSTEM MANAGER
RS-232
HEC
RS-485
CONTROL DATA
SCRAMBLER
24
SCRAMBLER
26
SCRAMBLER
28
EPG SCRAMBLER
TEXT CHAN SCRAMBLER
30
TEXT CHAN SCRAMBLER
32
CONTROL LINK
RS-232
SATELLITE OR MODEM LINK
EPG SUPPLIER
RS-232
INFORMATION SERVICES PROCESSOR
RS-485
EPG AND TEXT CHANNEL DATA
16
18
SATELLITE OR MODEM LINK
TEXT CHANNEL SUPPLIERS
RS-232
CABLE HEAD END
20
34
SET TOP TUNER
36
EPG MEMORY
38
TEMPLATE MEMORY
42
TEXT PAGE MEMORY
TV
40
STT TRANSACTIONS

Figure 28

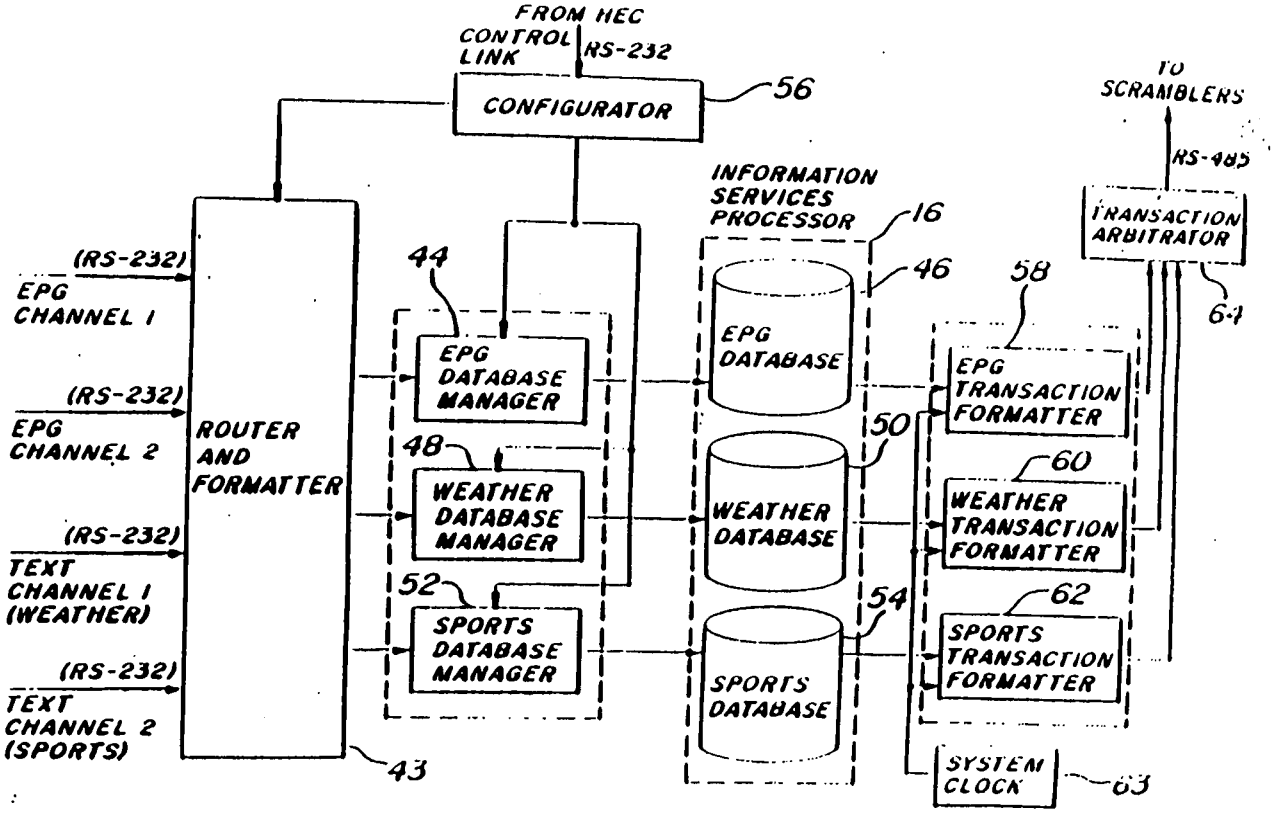

FROM HEC
CONTROL LINK
RS-232
CONFIGURATOR
56
TO SCRAMBLERS
RS-485
INFORMATION SERVICES PROCESSOR
16
TRANSACTION ARBITRATOR
61
(RS-232)
EPG CHANNEL 1
(RS-232)
EPG CHANNEL 2
(RS-232)
TEXT CHANNEL 1 (WEATHER)
(RS-232)
TEXT CHANNEL 2 (SPORTS)
ROUTER AND FORMATTER
43
44
EPG DATABASE MANAGER
48
WEATHER DATABASE MANAGER
52
SPORTS DATABASE MANAGER
46
EPG DATABASE
50
WEATHER DATABASE
54
SPORTS DATABASE
58
EPG TRANSACTION FORMATTER
60
WEATHER TRANSACTION FORMATTER
62
SPORTS TRANSACTION FORMATTER
SYSTEM CLOCK
63

Figure 29

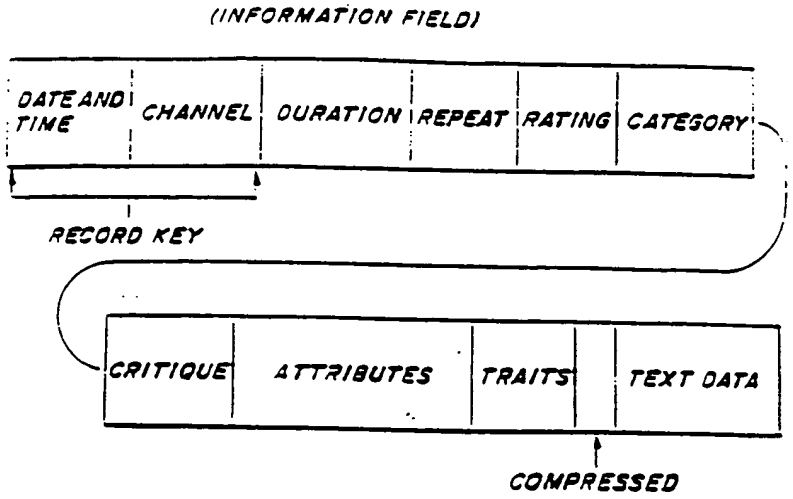


Figure 30

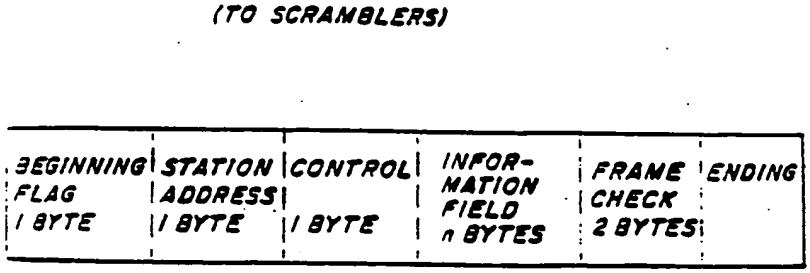


Figure 31

EPG TRANSACTION FORMATTER 58

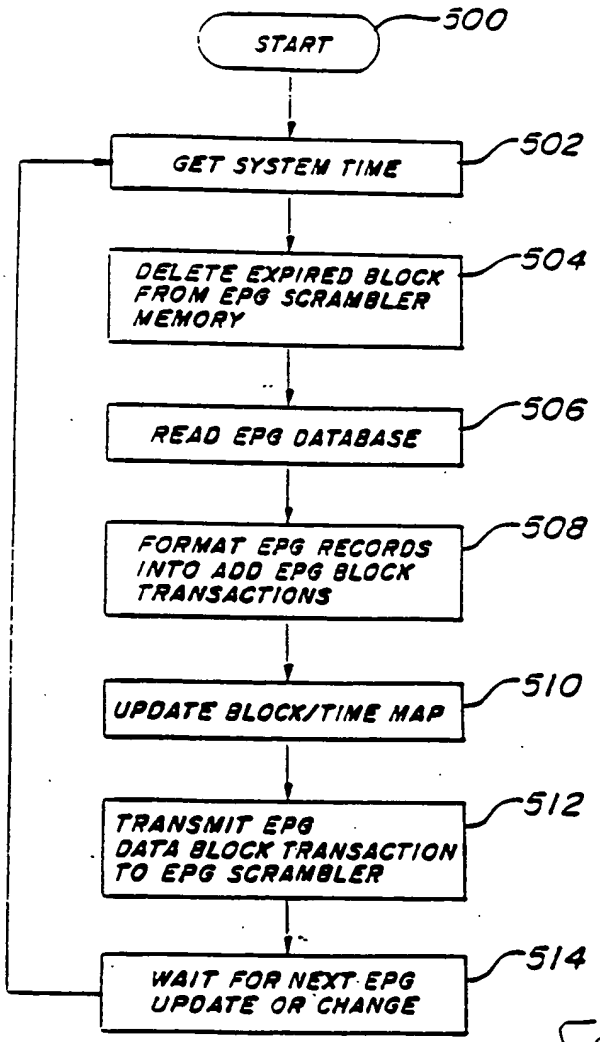


Figure 31

TEXT CHANNEL TRANSACTION FORMATTER 60, 62

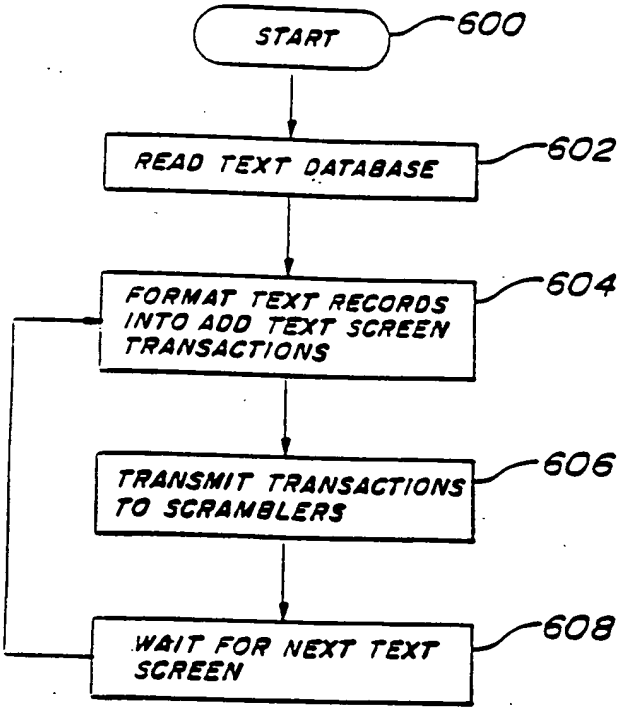


Figure 33

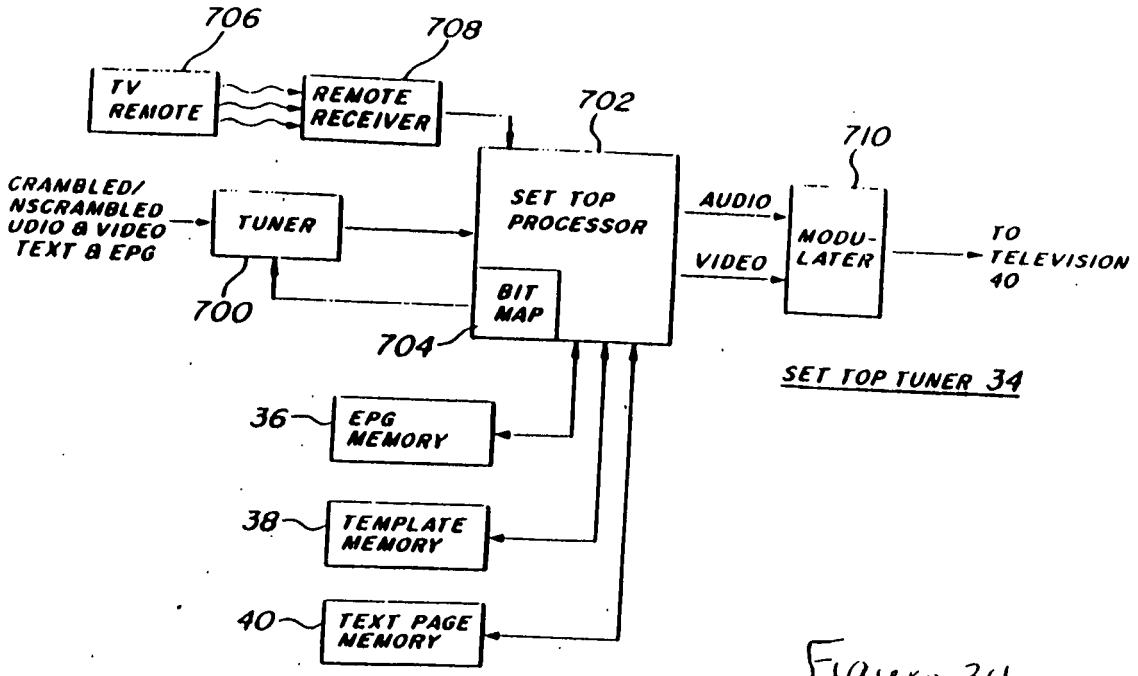

706
708
TV REMOTE
REMOTE RECEIVER
702
710
SCRAMBLED/ UNSCRAMBLED AUDIO & VIDEO TEXT & EPG
TUNER
SET TOP PROCESSOR
AUDIO
VIDEO
MODU-LATER
TO TELEVISION 40
700
BIT MAP
704
SET TOP TUNER 34
36
EPG MEMORY
38
TEMPLATE MEMORY
40
TEXT PAGE MEMORY

Figure 34

Process for automatically creating multiple profiles and automatically identifying currently active profiles

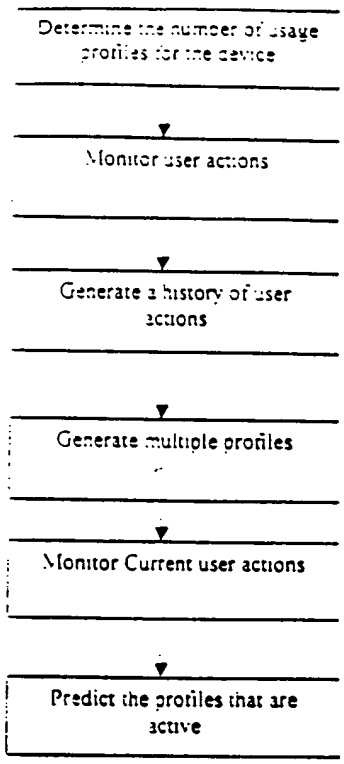


Figure 35

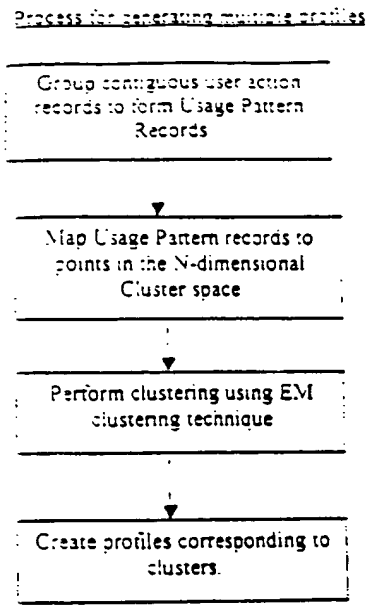
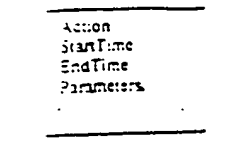
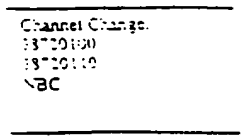

Process for generating multiple profiles
Group contiguous user action records to form Usage Pattern Records
Map Usage Pattern records to points in the N-dimensional Cluster space
Perform clustering using EM clustering technique
Create profiles corresponding to clusters.

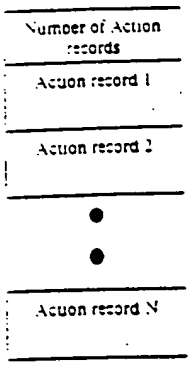
Figure 36



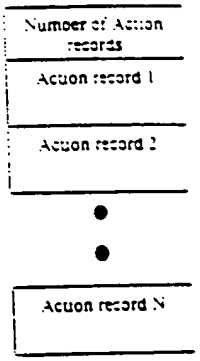
B) Format of user action record



B) Example of user action record

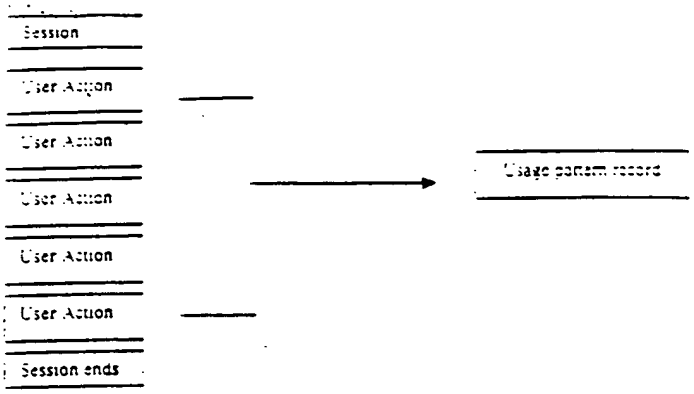


C) Format of History database

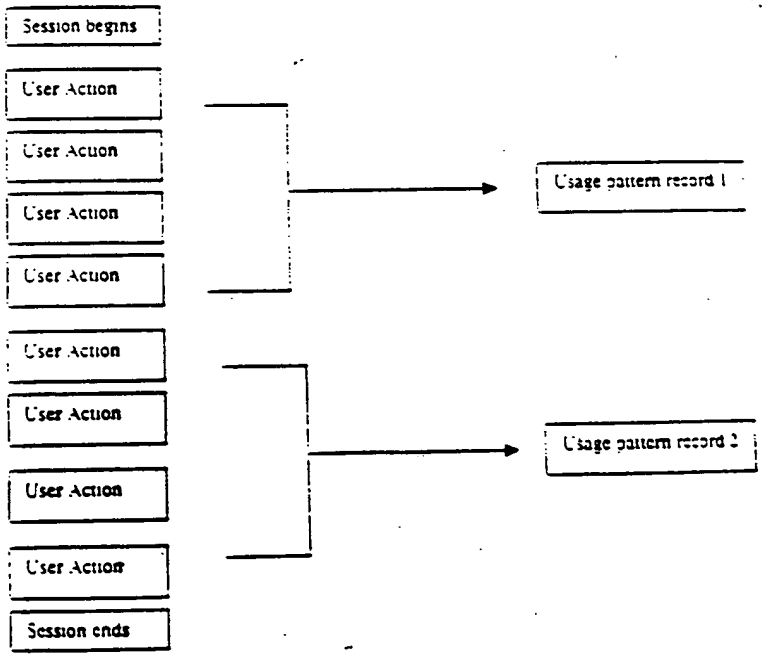


D) Format of Usage pattern record

Figure 37

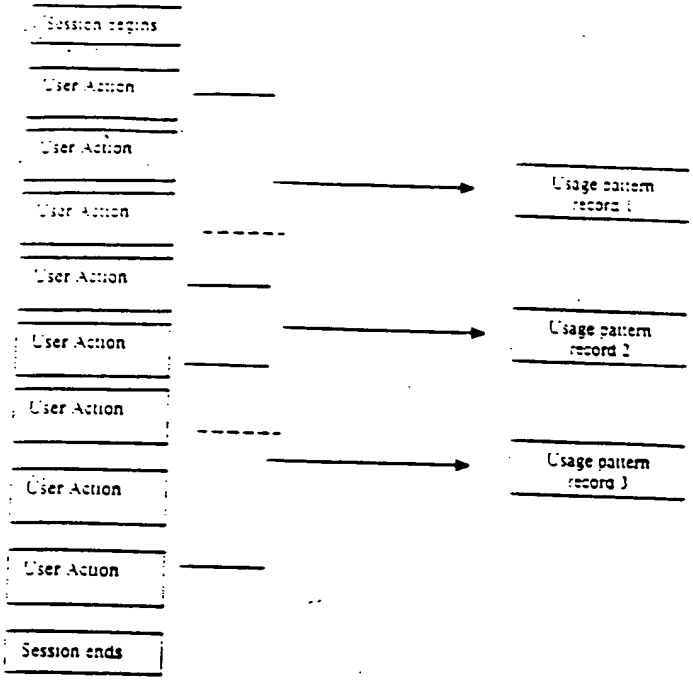


A) One method for creating usage pattern



B) One method for creating usage pattern

Figure 3B



One method for creating usage pattern record

Figure 10

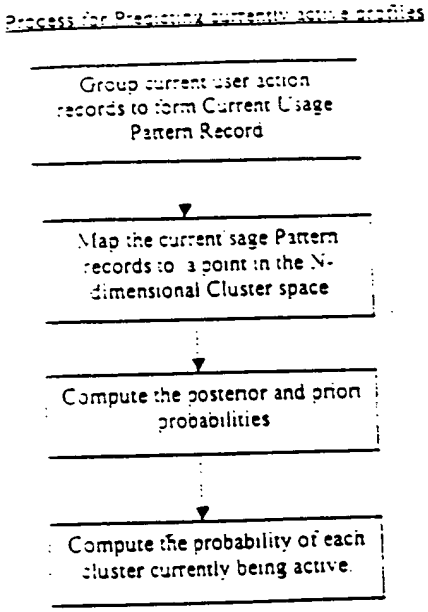

Process for Predicting currently active profiles
Group current user action records to form Current Usage Pattern Record
Map the current sage Pattern records to a point in the N-dimensional Cluster space
Compute the posterior and prion probabilities
Compute the probability of each cluster currently being active.

Figure 40

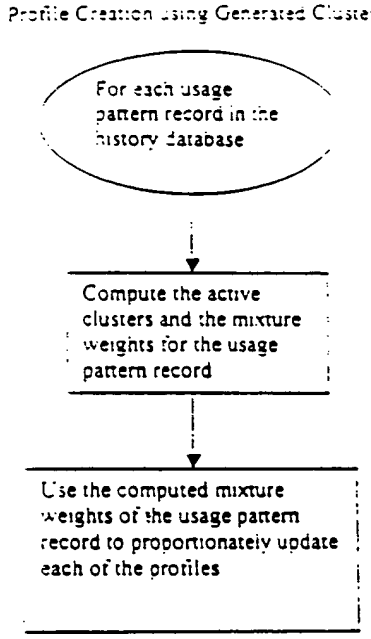

Profile Creation Using Generated Clusters
For each usage pattern record in the history database
Compute the active clusters and the mixture weights for the usage pattern record
Use the computed mixture weights of the usage pattern record to proportionately update each of the profiles

Figure 41

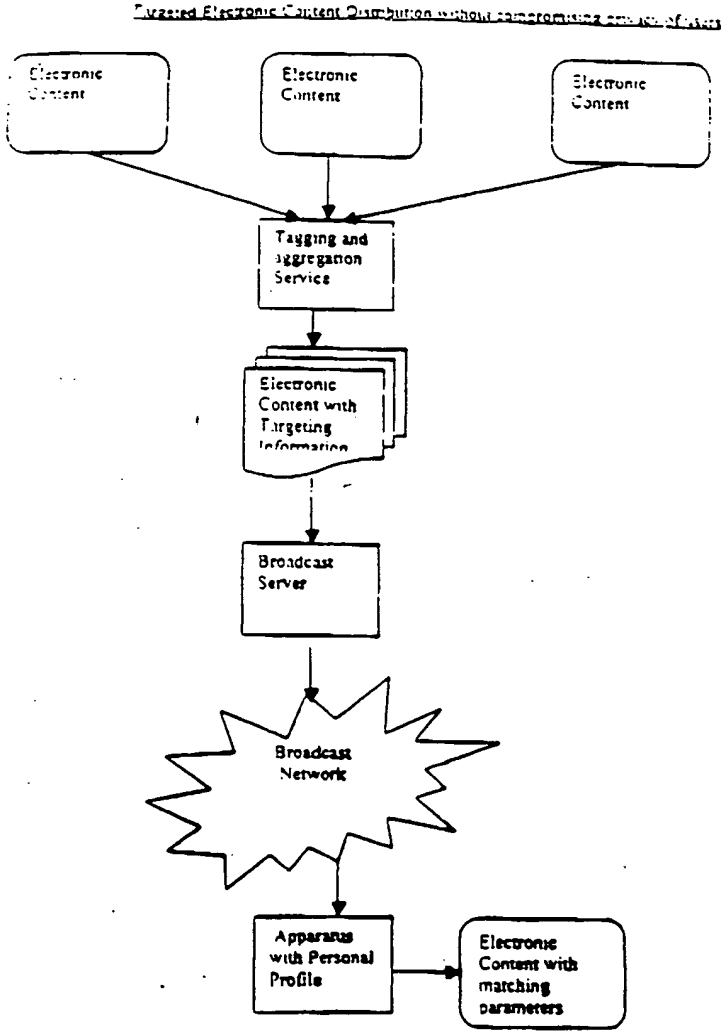
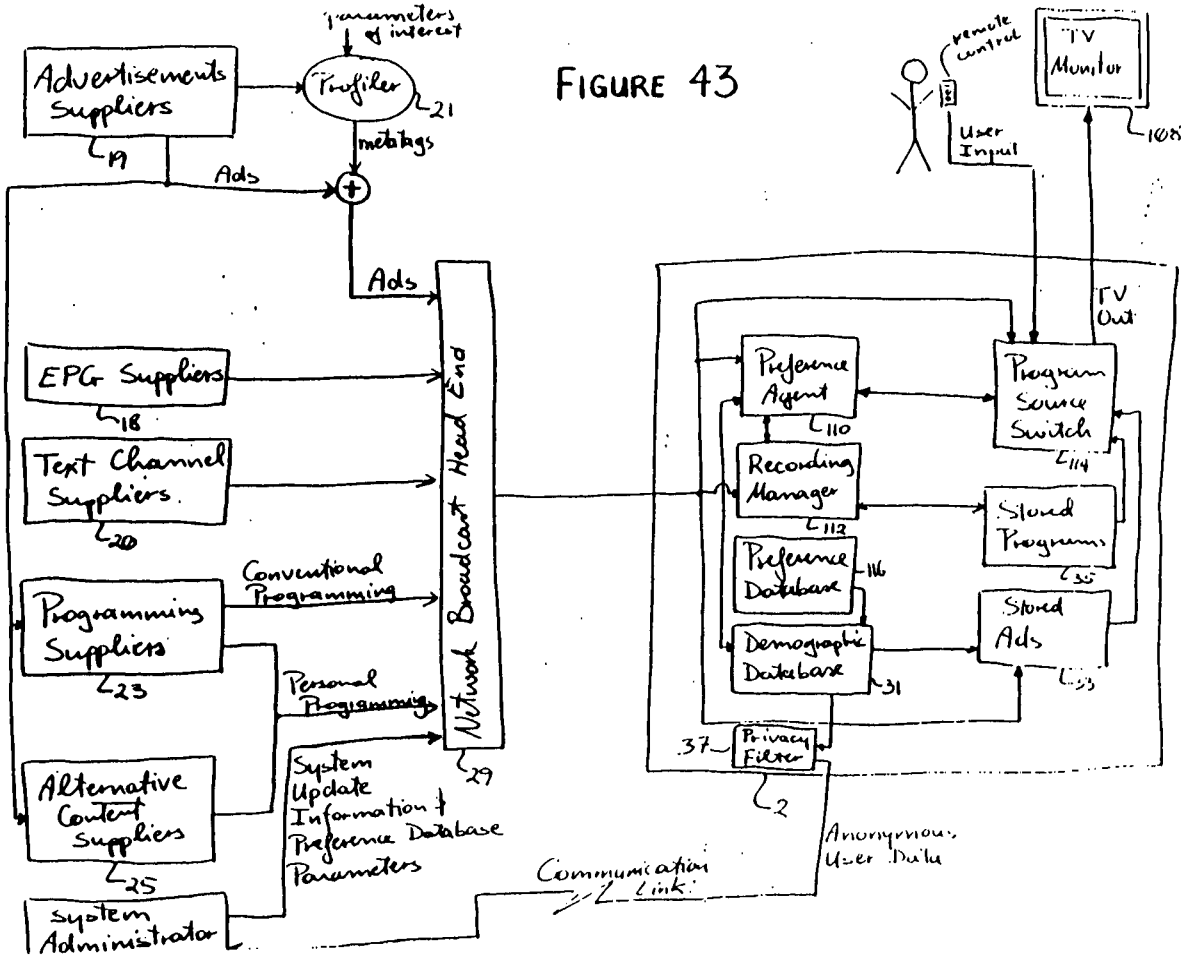

Electronic Content
Electronic Content
Electronic Content
Tagging and aggregation Service
Electronic Content with Targeting
Broadcast Server
Broadcast Network
Apparatus with Personal Profile
Electronic Content with matching parameters

FIGURE 42

FIGURE 43


parameters of interest
Advertisements Suppliers
19
Profiler
21
metatags
Ads
Ads
EPG Suppliers
18
Text Channel Suppliers
20
Conventional Programming
Programming Suppliers
23
Personal Programming
Alternative Content Suppliers
25
System Administrator
System Update Information + Preference Database Parameters
Network Broadcast Head End
29
Communication Link
2
remote control
User Input
TV Monitor
108
TV Out
Preference Agent
110
Recording Manager
112
Preference Database
116
Demographic Database
31
Privacy Filter
37
Program Source Switch
114
Stored Programs
35
Stored Ads
33
Anonymous User Data

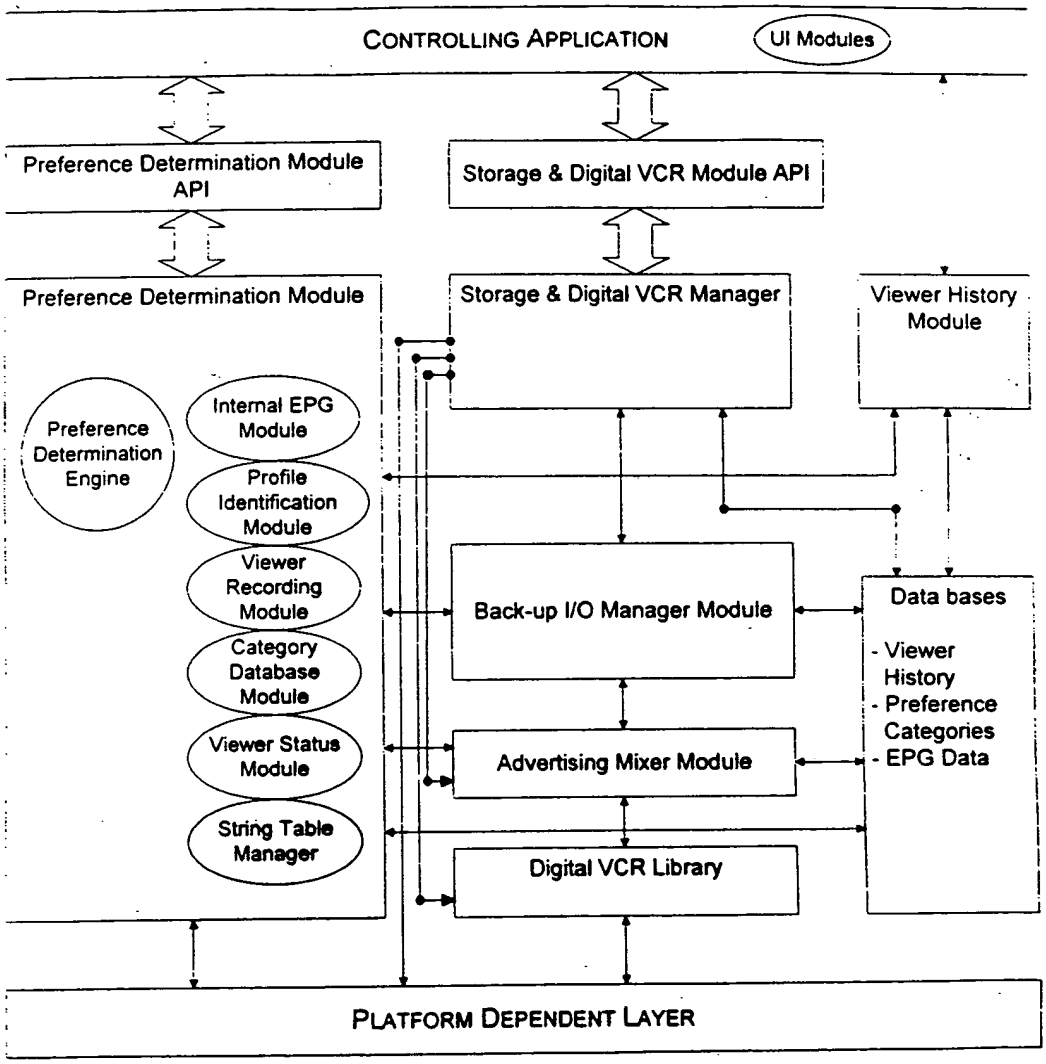

CONTROLLING APPLICATION
UI Modules
Preference Determination Module API
Storage & Digital VCR Module API
Preference Determination Module
Storage & Digital VCR Manager
Viewer History Module
Preference Determination Engine
Internal EPG Module
Profile Identification Module
Viewer Recording Module
Category Database Module
Viewer Status Module
String Table Manager
Back-up I/O Manager Module
Advertising Mixer Module
Digital VCR Library
Data bases
- Viewer History
- Preference Categories
- EPG Data
PLATFORM DEPENDENT LAYER

Figure 44.

Figure 45

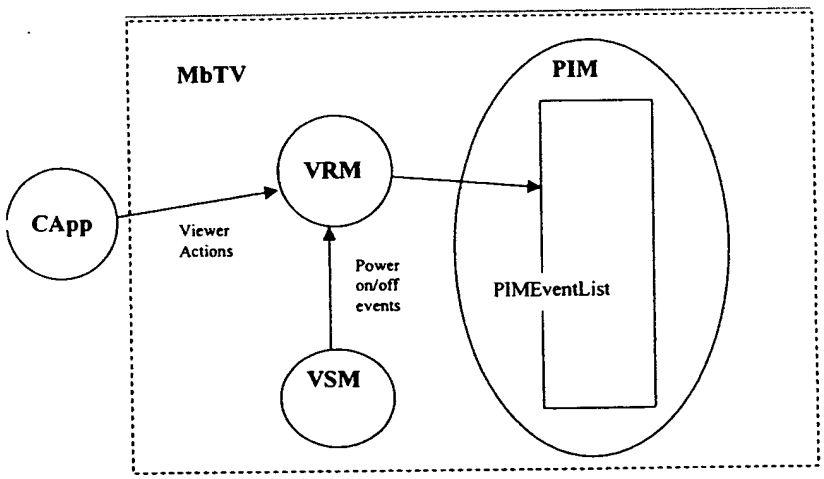

MbTV
PIM
VRM
CApp
Viewer
Actions
Power
on/off
events
PIMEventList
VSM

Figure 46

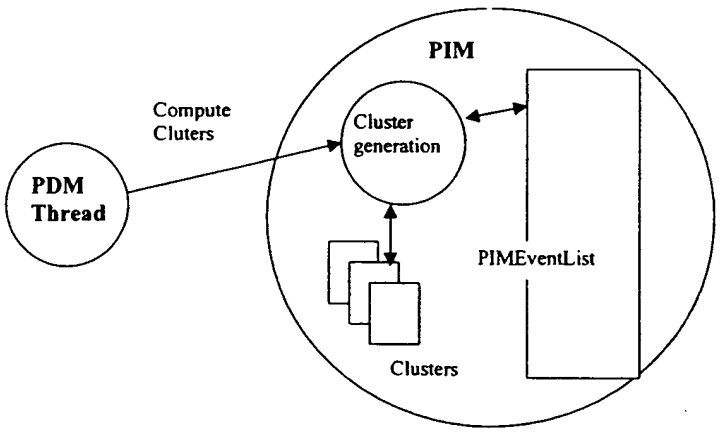
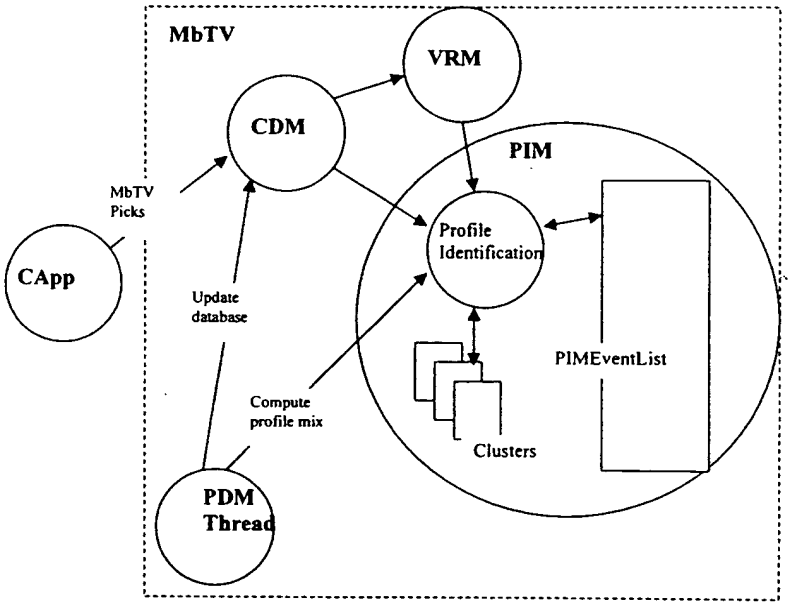

PIM
Compute
Cluters
Cluster
generation
PDM
Thread
PIMEventList
Clusters

Figure 47


MbTV
VRM
CDM
PIM
MbTV
Picks
CApp
Profile
Identification
Update
database
PIMEventList
Compute
profile mix
Clusters
PDM
Thread

PREFERENCE DETERMINATION ENGINE (PDE) ARCHITECTURE

Figure 4a

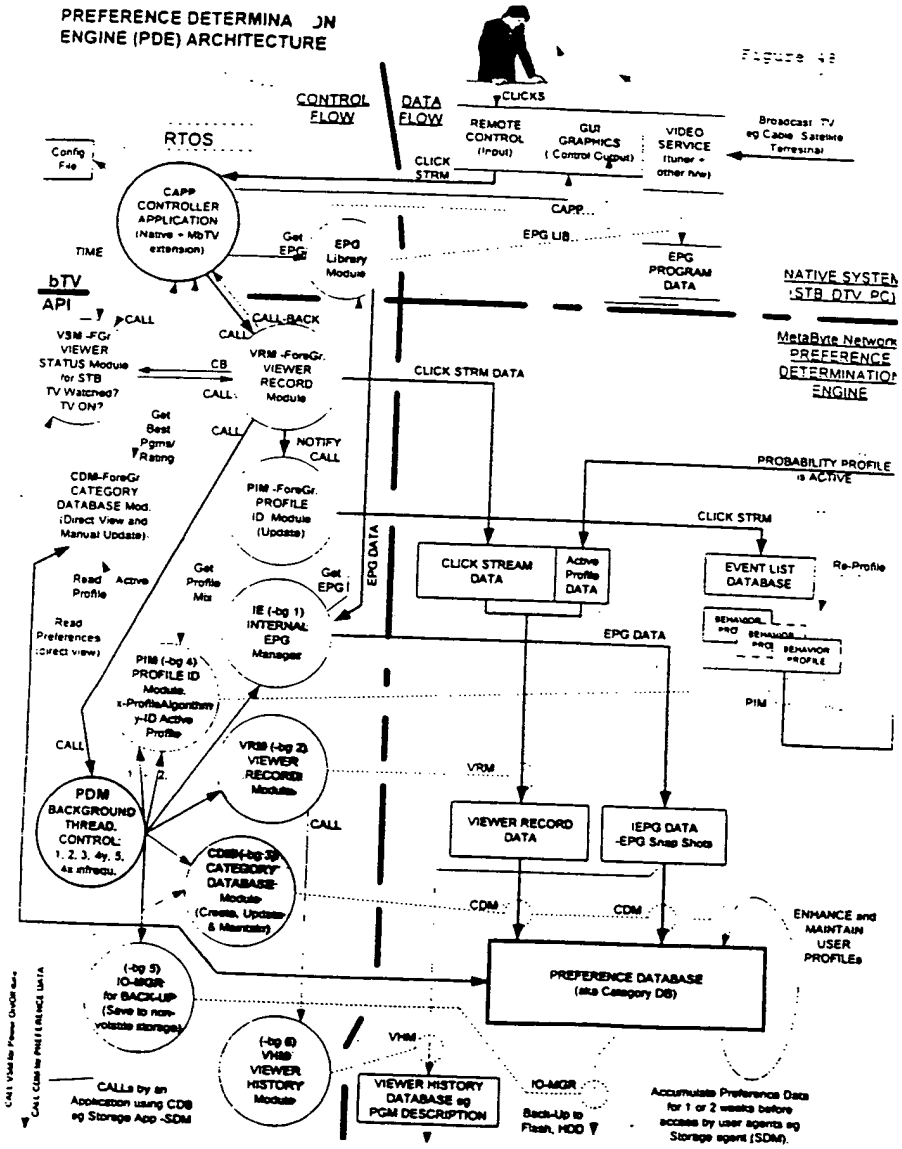
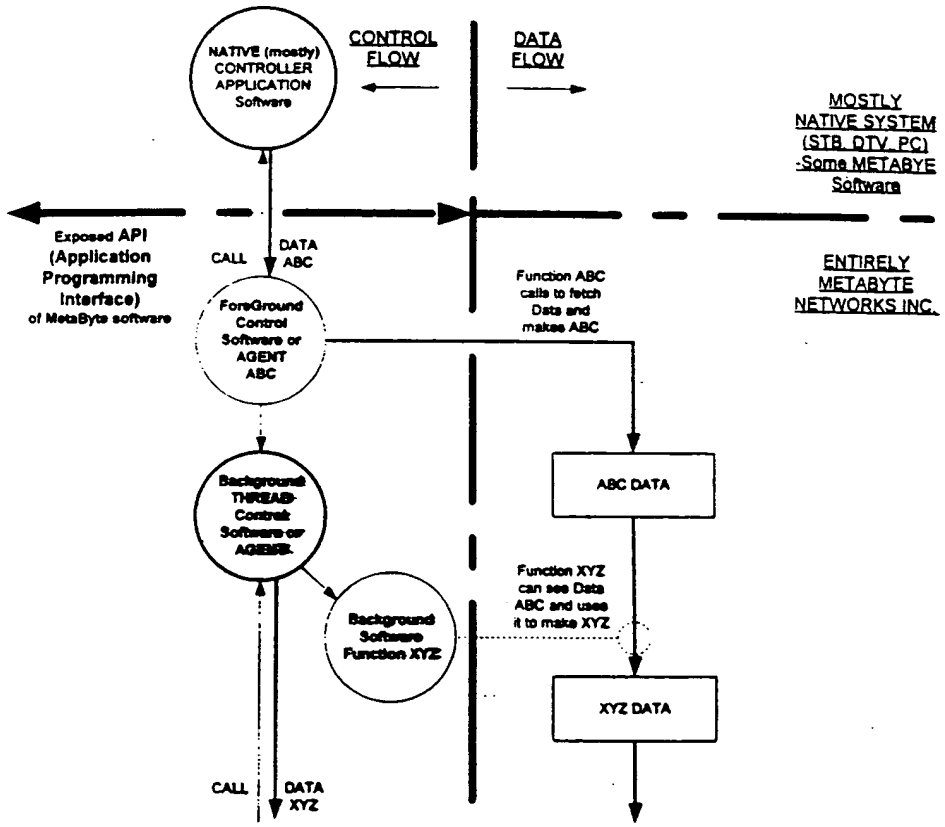


Figure 49


NATIVE (mostly) CONTROLLER APPLICATION Software
CONTROL FLOW
DATA FLOW
MOSTLY NATIVE SYSTEM (STB, DTV, PC) -Some METABYE Software
Exposed API (Application Programming Interface) of MetaByte software
CALL
DATA ABC
ENTIRELY METABYTE NETWORKS INC.
Function ABC calls to fetch Data and makes ABC
ForeGround Control Software or AGENT ABC
Background THREAD Control Software or AGENT
ABC DATA
Function XYZ can see Data ABC and uses it to make XYZ
Background Software Function XYZ
XYZ DATA
CALL
DATA XYZ

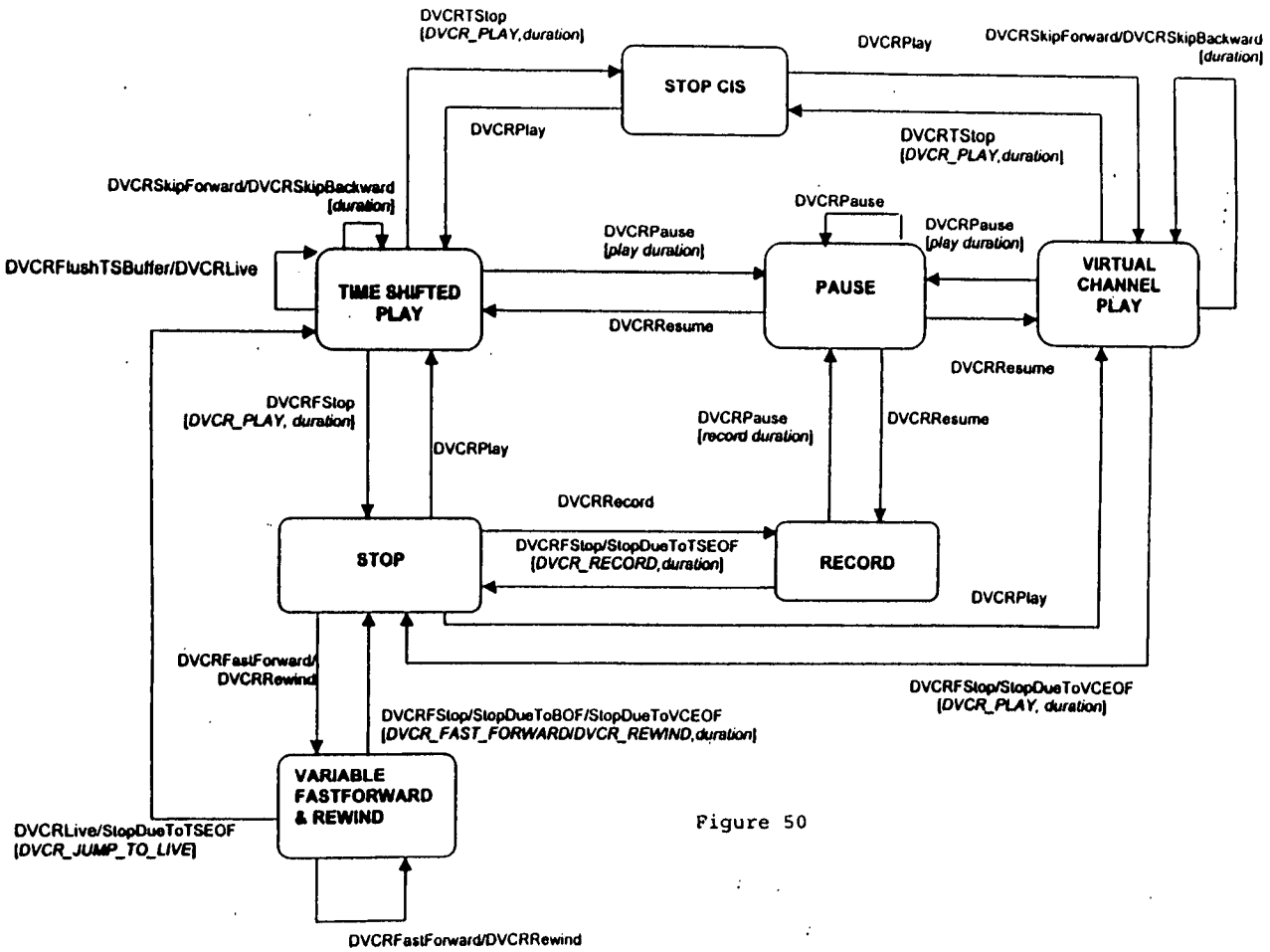

DVCRTStop
(DVCR_PLAY,duration)
STOP CIS
DVCRPlay
DVCRSkipForward/DVCRSkipBackward
(duration)
DVCRPlay
DVCRTStop
(DVCR_PLAY,duration)
DVCRSkipForward/DVCRSkipBackward
(duration)
DVCRPause
DVCRPause
(play duration)
DVCRPause
(play duration)
DVCRFlushTSBuffer/DVCRLive
TIME SHIFTED
PLAY
PAUSE
VIRTUAL
CHANNEL
PLAY
DVCRResume
DVCRResume
DVCRFStop
(DVCR_PLAY, duration)
DVCRPlay
DVCRPause
(record duration)
DVCRResume
DVCRRecord
STOP
DVCRFStop/StopDueToTSEOF
(DVCR_RECORD,duration)
RECORD
DVCRPlay
DVCRFastForward/
DVCRRewind
DVCRFStop/StopDueToVCEOF
(DVCR_PLAY, duration)
DVCRFStop/StopDueToBOF/StopDueToVCEOF
(DVCR_FAST_FORWARD/DVCR_REWIND,duration)
VARIABLE
FASTFORWARD
& REWIND
DVCRLive/StopDueToTSEOF
(DVCR_JUMP_TO_LIVE)
DVCRFastForward/DVCRRewind

Figure 50

Figure 51

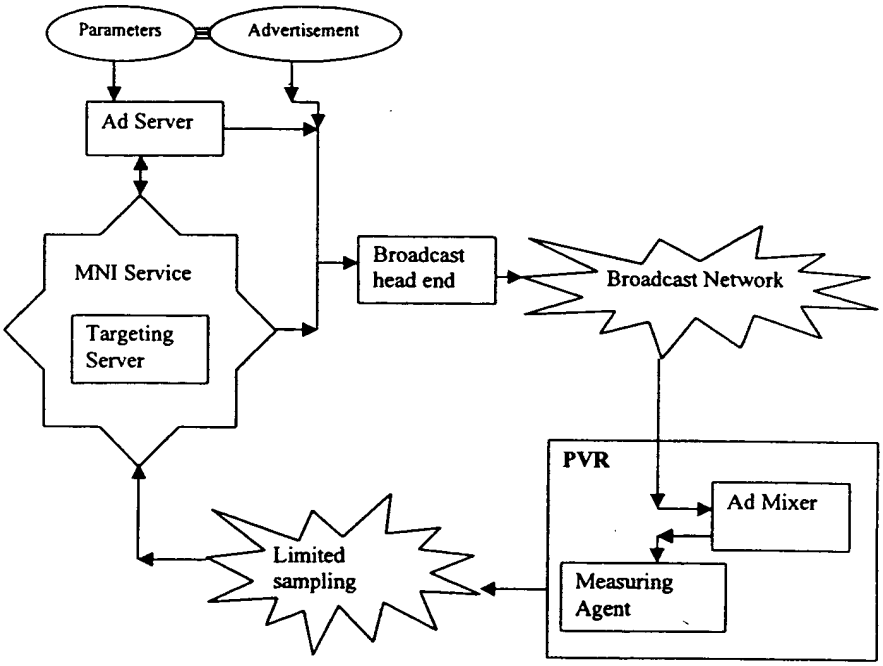

Parameters
Advertisement
Ad Server
MNI Service
Targeting Server
Broadcast head end
Broadcast Network
PVR
Ad Mixer
Measuring Agent
Limited sampling

Figure 52

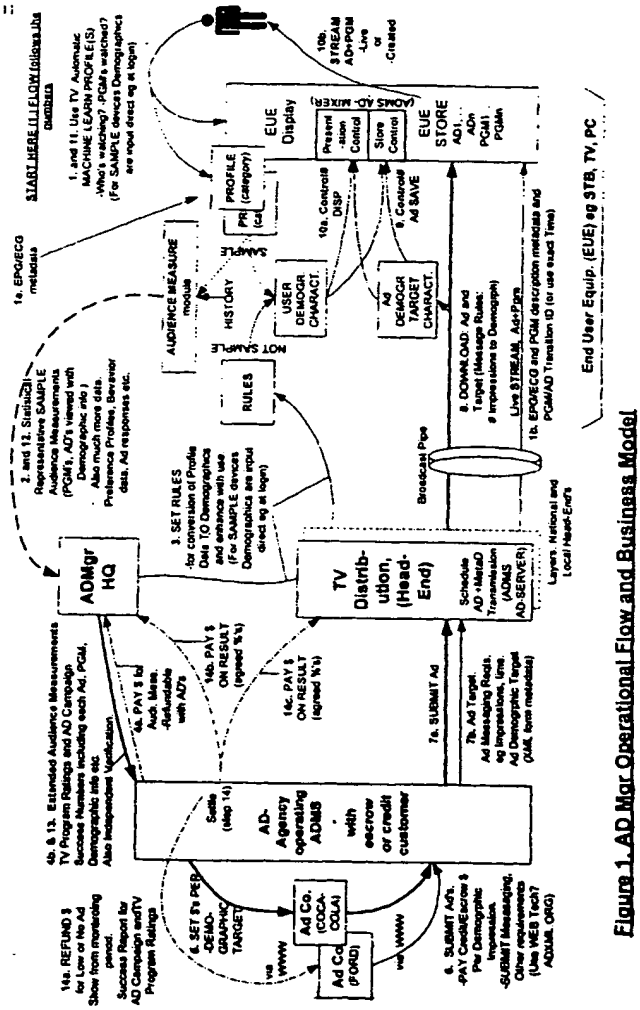


Figure 1. AD Mgr Operational Flow and Business Model

Figure 53

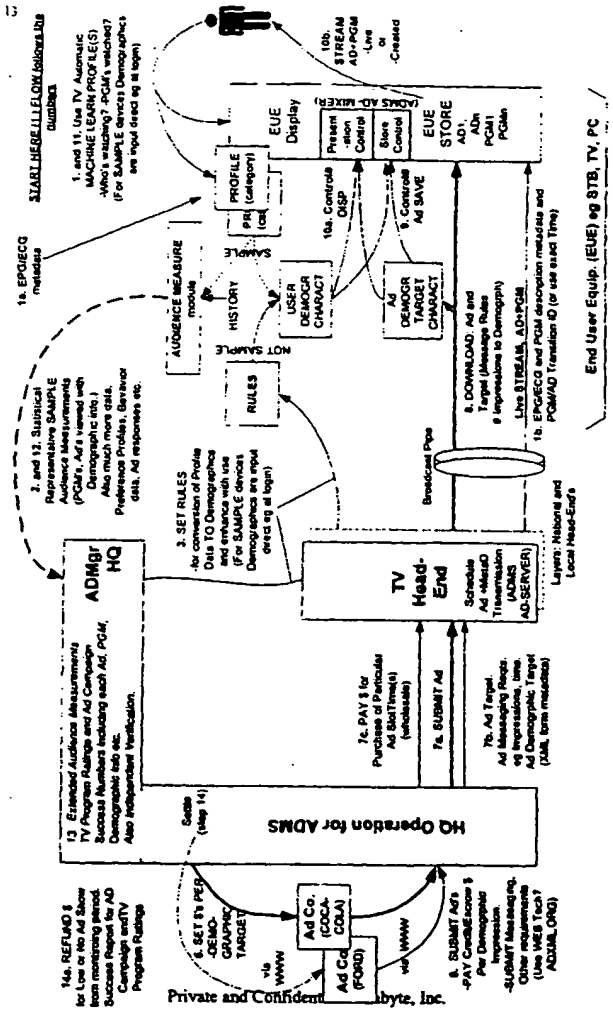


Figure 2. AD Mgr Operational Flow and Business Model 2